**Music Similarity Models applied to
Cover Song Identification and Classification**

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Abstract

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The spread of digital music allowed the appearance of datasets with millions of music files. The processing of this huge number of audio files is carried out with techniques of Music Information Retrieval (MIR) that work directly with the audio content. The MIR task of most interest in this project is the modelling of Music Similarity. Our proposed approach follows this pipeline: extract audio features, aggregate local features into global features, and compute the similarities of every pair of songs from the dataset being processed. According to this approach, a triple $\{\text{extractor}_i, \text{aggregator}_j, \text{distance}_k\}$ defines a music similarity model, and our main goal is to investigate the ability of similarity models to distinguish audio files from different classes. The music similarity models are also used to address specific problems such as Cover Song Identification (CSI), which is an MIR application related to Music Similarity, and the closely-related Cover Song Classification (CSC) problem. MIR-related techniques, such as Dataset Modifications and Matrix Fusion, are explored in the context of improving the results of music similarity models. This work presents several contributions, among which a comprehensive benchmark of music similarity models; the definition of new similarity matrices within CSC as a solution approach to the CSI problem; the exploration of different types of dataset modifications and an investigation of their effect on music similarity metrics; and the fusion of similarity matrices computed from secondary datasets obtained via source separation. The experiments presented produced encouraging results, indicating that the methods proposed in this thesis point towards novel approaches to Music Similarity that are worth further investigation and development.

Keywords: computer music, music information retrieval, music similarity, cover song identification, cover song classification.

Resumo

BODO, R. P. P. **Modelos de Similaridade Musical aplicados à Identificação e Classificação de Covers**. 2021. 165 f. Tese (Doutorado) - Instituto de Matemática e Estatística, Universidade de São Paulo, São Paulo, 2021.

A difusão da música digital permitiu o surgimento de conjuntos de dados com milhões de arquivos de áudio. O processamento deste enorme número de arquivos é realizado com técnicas de Recuperação de Informação Musical que analisam diretamente o conteúdo do áudio. A tarefa de maior interesse neste projeto é a modelagem de Similaridade Musical. Nossa proposta segue os seguintes passos: extrair descritores de áudio, agregar descritores locais em descritores globais e calcular as distâncias entre todos os pares de músicas dos conjuntos de dados sendo processados. De acordo com essa abordagem, uma tripla $\{\text{extrator}_i, \text{agregador}_j, \text{distância}_k\}$ define um modelo de similaridade musical, e nosso principal objetivo é investigar a capacidade dos modelos de similaridade de distinguir arquivos de áudio de classes diferentes. Os modelos de similaridade musical também são usados para resolver problemas específicos, como Identificação de Covers, que é uma aplicação de Similaridade Musical, e Classificação de Covers, que é um problema relacionado com o de Identificação. Outras técnicas de Recuperação de Informação Musical, como Modificação de Conjuntos de Dados e Fusão de Matrizes, são exploradas no contexto de melhorar os resultados de modelos de similaridade musical. Este trabalho apresenta várias contribuições, entre as quais o benchmark de modelos de similaridade musical; a definição de novas matrizes de similaridade no contexto de Classificação de Covers como abordagem de solução para a Identificação de Covers; a exploração de diferentes tipos de modificação de conjuntos de dados e uma investigação de seus efeitos nas métricas de similaridade musical; e a fusão de matrizes de similaridade calculadas a partir de conjuntos de dados secundários obtidos por meio de separação de fontes. Os experimentos apresentados produziram resultados encorajadores, indicando que os métodos propostos nesta tese apontam na direção de abordagens inovadoras que merecem investigação e desenvolvimento adicionais.

Palavras-chave: computação musical, recuperação de informação musical, similaridade musical, identificação de covers, classificação de covers.

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Acronyms

CENS Chroma Energy Normalized Statistics. 8, 61, 90, 91, 107

CQT Constant-Q Transform. 6, 7, 61

CSC Cover Song Classification. 3, 4, 45–47, 63, 64, 67, 68, 73, 98, 101, 107–109, 117, 134

CSD Cover Song Detection. 37

CSI Cover Song Identification. 3, 4, 37, 38, 40–42, 44, 45, 51, 54, 56, 62, 63, 65, 67, 68, 72, 73, 83, 84, 93, 96–99, 101, 102, 108, 109, 116, 117, 121, 127, 133–136

CSM Cross-Similarity Matrix. 41, 42

CSR Cover Song Retrieval. 37

DCT Discrete Cosine Transform. 9

DPLA Dynamic Programming Local Alignment. 56

DTW Dynamic Time Warping. 38, 40, 54, 56, 135

EDM Electronic Dance Music. 79

EMD Earth Mover’s Distance. 31

GMM Gaussian Mixture Model. 24, 39, 40, 61

HMM Hidden Markov Model. 70

HPCP Harmonic Pitch Class Profile. 37, 38, 41, 42, 46, 51, 56

IICSR Intra-Inter Class Similarity Ratio. 87, 89–92

KL Kullback-Leibler. 30

KNN K-Nearest Neighbors. 41

LCS Longest Common Subsequence. 29, 61, 92, 97

MAP Mean Average Precision. 45, 62, 67, 93, 120, 134

MDR Median Rank. 45, 62, 67, 93

MFCC Mel-Frequency Cepstral Coefficients. [3](#), [9](#), [41](#), [42](#), [50](#), [51](#), [59](#), [61](#), [70](#), [75](#), [90](#), [91](#)

MIDI Musical Instrument Digital Interface. [17](#), [26](#)

MIR Music Information Retrieval. [1](#), [3](#), [5](#), [69](#), [82](#)

MLP Multi-Layer Perceptron. [46](#)

MR Mean Rank. [44](#), [45](#), [62](#), [65](#), [67](#), [93](#), [112](#), [116](#), [117](#), [120](#), [126](#), [134](#), [135](#)

MRR Mean Reciprocal Rank. [44](#), [45](#), [62](#), [67](#), [93](#)

NMF Non-negative Matrix Factorization. [70](#)

OTI Optimal Transposition Index. [41](#), [62](#), [91](#), [97](#), [98](#), [134](#)

PCA Principal Component Analysis. [70](#)

PLCA Probabilistic Latent Component Analysis. [70](#)

RMS Root Mean Square. [3](#), [15](#), [50](#), [59](#), [61](#), [71](#), [134](#)

SHS Sub-Harmonic Summation. [40](#)

SI-PLCA Shift-Invariant Probabilistic Latent Component Analysis. [70](#)

SNF Similarity Network Fusion. [41–43](#), [73](#), [123](#), [126](#)

SOM Self-Organizing Map. [135](#)

SSM Self-Similarity Matrix. [40–42](#), [70](#)

STFT Short-Time Fourier Transform. [5](#), [6](#), [8](#), [61](#)

SVM Support Vector Machine. [46](#)

THPCP Transposed Harmonic Pitch Class Profile. [38](#)

ZCR Zero Crossing Rate. [16](#), [50](#), [51](#), [59](#), [61](#)

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Chapter 1

Introduction

1.1 Context and Motivation

The dissemination of digital music has enabled the grouping of thousands of audio files (in personal collections) or millions of files (in databases of stream web-sites or online music stores). For instance, the company Spotify¹ provides 70 million tracks to its users².

Traditionally, searches on these datasets are done by objective terms (such as artist, album, track, year, record label, etc) or subjective (such as style, genre, etc). Searching with metadata can be interesting, but it has some inherent problems. For instance, the cold start problem: how to start the tagging process for a newly created dataset or for recently added audio files to a pre-existing database.

Some solutions used in the past are assignments by experts (as Pandora³ did) or by collective intelligence (as Last.fm⁴ did). However, both solutions have problems. When working with a team of specialists there is a high maintenance cost and, in addition, an intrinsic reduced speed of manual classification.

Regarding the classification by users, there is the bias created by communities with their own language and unique point of view when labeling the presented songs. In addition, there is the fairness problem: the most popular artists are classified before and in greater quantity, which makes them more prominent than unknown artists (who could be the most suitable answer to a search).

A second problem of searching (or browsing) with metadata is the limitation of the terms used. There is no consensus on which tag should be assigned to each song (or album, or artist), and also that it must be unique. Such attribution complexity generates a multitude of problems, such as the inability to fully capture the cultural context and the musical content of the tracks. Moreover, it is somewhat difficult for the lay public to assimilate the meaning of each tag, and it takes a while for the user to be able to search effectively.

For these and other reasons it has been an increasingly common practice to use **Music Information Retrieval (MIR)** techniques to deal with huge databases. The act of working directly with the audio and the musical contents has several advantages and this is the global goal of that research area.

MIR techniques can provide to the user the ability to hum to retrieve a melody, or to clap to fetch a rhythm, or even to use an audio file as the query object and receive similar tracks in response. The goal is to make content more accessible and in a more intuitive way.

The **MIR** task of most interest in this project is the Music Similarity one. Giving an annotated dataset, it is possible to calculate how similar are the songs within it (or to an external song) with the use of music similarity models. Thus, a solid foundation for navigation, organization, recommendation, and search in this database is created.

¹<https://www.spotify.com/>

²<https://newsroom.spotify.com/company-info/>

³<http://pandora.com/>

⁴<http://last.fm/>

Since there is no universally agreed-upon formalized concept of general musical similarity, our approach to this problem is to deal with its individual aspects. Some important perceptual properties of sound are pitch, duration, intensity and timbre. So similarities related to these properties are addressed: melodic, harmonic, rhythmic, dynamic, timbre, etc. It is important to explicitly state that the idea of music similarity completely depends on the context, which usually is established by the dataset and the application. We present a few examples below:

- query-by-humming

In this application the user has a melody in mind and makes a search for similar melodies humming it. Such a task benefits from melodic similarity models tolerant to changes in pitch, duration, and also the addition, deletion, and substitution of notes from the sought melody.

- automatic DJing

This application is directly linked to the automatic generation of playlists. However, the songs are appended in such a way that their tempi are equal. The onsets need to be synchronized, and the transitions between tracks should be as smooth as possible (no silences or breaks are allowed). Automatic DJing definitely benefits from rhythmic similarity models selecting tracks that can better mixed one after the other.

- recognition of musical instruments

The user may want to find all the songs on which there is a flute being played, or a trombone, or a harmonica. Maybe he wants to find a specific ensemble such as a string quartet (with two violins, a viola and a cello) or a jazz trio (with piano, bass and drums). Searches with these characteristics can be addressed by timbre similarity models.

The literature on audio-based music similarity presents several approaches, including the use of traditional information retrieval methods (such as extracting features from audio recordings, and computing their distances in a vector space) [Foo97, LO04, SSPK10, YZL⁺10, KS13, Tra17]; modeling the extracted features distributions and comparing the models [LS01, AP⁺02, PA04, BLEW04, TWV05, SFW12]; feature learning [PBD⁺16, YXC20]; metric learning [SWW08, HKKL17]; deep neural networks [MSC19, FR21]; among others.

1.2 Problems addressed and Goals

The research presented here focuses on representations of musical content, and more specifically human-readable representations. This allows for a kind of audit of what happens at each stage of the modelling of music similarity, and how these models are used in specific tasks. We are mainly interested in offering tools that allows one to explain and understand exactly how music similarity models produce their scores, independently of how these models perform in those tasks. This focus on fully-explainable human-readable models and a desire to approach a multitude of alternative similarity models takes precedence over a quest for the highest achievable performance metrics.

Music Similarity

The main problem we address is the modelling of music similarity and the assessment of its quality. Our proposed approach, which generalizes the first two approaches above, is based on the following pipeline [KS16]: extract audio features, aggregate local features into global features, and compute the similarities of every pair of songs from the dataset being processed. A triple $\{extractor_i, aggregator_j, distance_k\}$ defines a music similarity model, and our main goal is to investigate the capacity of similarity models to distinguish tracks from different classes in selected datasets.

Regarding the feature extractors, we work with tonal features, such as chromagrams [JCEJ08, SGHS08, YZL⁺10, RE10], tonnetz [Tym09], and symbolic melodic sequences [GLCS95, TYW⁺05,

FM05, Mar06, RH06a, SSG13a]. Also with timbre features (Mel-Frequency Cepstral Coefficients (MFCC) [Foo97, LS01, AP⁺02, BLEW04, PA04, SFW12]), spectral features [LO04] (spectral centroid, bandwidth, contrast, flatness, etc), rhythmic features (Rhythm Pattern [PRM02a, PFW⁺05, SSPK10]), dynamic features (Root Mean Square (RMS) [PT05, MF05]), and others.

Some of the aggregation techniques we employ are single Gaussian [SFW12], Gaussian Mixture Model [AP⁺02, PA04, BLEW04], Vector Quantization [LS01], Markov Chain [HRG01], Octave Abstraction [SSG13a], Interval Abstraction [SSG13a], Pitch Contour (3-levels) [GLCS95], Pitch Contour (5-levels) [RH06a].

Lastly, the list of distances we use includes Manhattan distance [SSPK10, KS13], Euclidean distance [Foo97, LO04, YZL⁺10], Cosine distance [Foo97, Tra17], LCS-based distance [UZ99, Kel12], Levenshtein's distance [LU00, Kel12], Kullback-Leibler distance [BLEW04, SFW12], Earth Mover's distance [LS01, TWV05], Monte Carlo distance [AP⁺02, PA04].

Cover Song Identification

Alternatively, instead of looking for the music similarity problem as a “pure” problem, we also address one of its application: **Cover Song Identification (CSI)**. This application involves identifying songs which are versions of each other, and it assumes that the covers of a given song must have some common music trait, which would be captured by a music similarity model.

Several papers from the CSI literature state that the best results can be achieved with tonal similarity, since the tonal aspects are the least likely to vary between version songs [SGH10, SSG12, CLX17]. Several projects use tonal features [GHO06, JCEJ08] or symbolic sequences [TYW⁺05, Mar06]. Also it can be found that state-of-the-art CSI methods uses at least one type of (early or late) fusion [Tra17, CLX18].

The main goal of our approach to the CSI problem is quite similar to the one of the music similarity problem: we want to investigate the models that are best suited to distinguish groups of songs that are versions from groups of songs that are not. Regarding fusion methods, we use them in a distinct way than the one found in the literature, as will be fully explained in Section 5.5.

Cover Song Classification

The **Cover Song Classification (CSC)** problem, which is a sibling to the CSI problem, is also investigated. CSI produces ranked lists of version candidates with values between 0 and 1 determining the similarity scores between the query song and the songs in the database; CSC assigns 0 or 1 for a pair of songs (binary classification) saying if they are versions of each other. The literature for CSC is not as vast as the one for CSI, but a couple of papers could be identified [RE10, SSG12].

Our approach to the CSC problem basically consists in using the music similarity pipeline cited above to compute several similarity values (using several distinct models) between all pair of songs from a dataset, and use them to compose samples to the binary classification process. This is designed in order to exploit different points of view about that pair of songs. Our main goal here is to find out the best set of models that can achieve the best classification metrics.

We also explore the very promising bridge between CSI and CSC. Every trained classifier can be asked to return the chance of a pair of songs to be versions, instead of the usual binary classification value 0 or 1. Our approach to link the CSC problem with CSI one is to obtain all these chance values for all pair of songs from a dataset, and build a new similarity matrix (as if we had a new music similarity model). Our main goal here is to check how this brand new similarity matrix can help to identify songs that are versions of each other from songs that are not.

Dataset Modifications

Finally we explore one last MIR-related method - dataset modification - applied to the CSI problem. Several remarks can be found in the literature about audio files modifications being used in

order to obtain better results, or even to decrease processing time (when the modification technique returns a smallest representations of the audio files).

The main goal is to generate brand new secondary datasets using this modification methods, and check if it is possible to obtain better results for the [CSI](#) problem, compared to the ones obtained with the original datasets. As a bonus, we can also obtain better processing times with the derivative datasets (with a few specific cases). This is a very important aspect since the process of comparing every pair of songs from a dataset is already an expensive task (if N is the number of tracks, the complexity is $O(N^2)$) and everything we can do to mitigate the time bottleneck is very promising.

Three main types of dataset modifications we experiment with are: frame selection [[Sey10a](#)], segment selection [[LS06](#), [BPVT08](#), [SdSB15](#)], and source separation [[FDLR10](#)]. Roughly, the first one discards a few frames from the audio files based on the injure they can potentially cause to the similarity computations; the second type replaces the full-length audio files to a fixed-length segment (for instance, 30 seconds); the later uses isolated sources (such as vocals, bass, drums, etc) in place of the whole mixtures.

1.3 Thesis contributions and structure

The main contributions of this thesis are:

- a comprehensive benchmark of music similarity models;
- a comparative discussion on related similarity models;
- an open-source music similarity framework;
- novel alternative ways to build samples for [CSC](#);
- a new heuristic for train/test split;
- an experiment connecting the [CSI](#) and [CSC](#) problems;
- a comprehensive exploration of distinct dataset modifications and the proposal of novel dataset modification techniques;
- the use of source separation for dataset modifications and fusion of music similarity models;
- the study of theoretical performance bounds for the family of similarity models considered.

The remaining of this thesis is structured as follows: Chapter [2](#) presents the extractors, aggregators and distances to compose the considered music similarity models; Chapter [3](#) introduces all the works related to our approaches to Cover Song Identification and Classification; Chapter [4](#) gives all details about projects that use dataset modifications; Chapter [5](#) presents our individual approaches to every problem considered in this thesis; Chapter [6](#) displays the design and results of each one of our experiments; Chapter [7](#) shows our final conclusions and future works.

Chapter 2

Music Similarity

2.1 Feature extractors

Despite the recent emergence of waveform-based music processing with deep learning [DS14, ODZ⁺16, PNP⁺17], it is not common to use audio signals directly as samples of a Music Information Retrieval (MIR) task. Usually, alternative representations, called audio features or descriptors, are used. One of the main reasons is to avoid high dimensionality problems [Bel57], because time-domain audio vectors are very large (30 seconds sampled at 44100Hz has over 1 million samples). Another reason is to highlight some kind of information contained in the audio signal, but not automatically (or trivially) deduced by the machine.

Choosing which features are extracted and used is therefore essential to solve a problem. Depending on the nature of the problem, we want to work with different music information, and audio features correlated with this information help the algorithms to get better results. In this section we present all the audio features used for the music similarity computations in our project.

Chromagram STFT-based

Pitch is made of two components: chroma and tone height [Mül15]. The chroma is a value in the set {C, C#, D, D#, E, F, F#, G, G#, A, A#, B}, and the tone height is a numeric value relative to the octave number. The pitches that have the same chroma form a group called pitch class, and a chromagram is a feature that aggregates the energy of all pitches of the same pitch class.

The chromagram is created from the spectrogram accumulating the amplitude of the bins associated to the same pitch class. The final result is a matrix with 12 rows (relative to all pitch classes) and the number of columns equal to the number of processed time frames. The chromagram referred to as *chroma_stft* in this text is specifically build using the Short-Time Fourier Transform (STFT) spectrogram [Ell07a]. Figure 2.1 shows an example spectrogram, Figure 2.2 shows the filter bank that maps the bins to pitch classes, and Figure 2.3 shows the resulting STFT-based chromagram obtained by the dot product of the spectrogram by the filter bank (followed by a normalization step).

Figure 2.1: *STFT spectrogram from a C-major scale sample performed by a piano.*

Figure 2.2: *Filter bank that maps STFT-bins to pitch classes.*

Figure 2.3: *STFT-chromagram from a C-major scale sample performed by a piano.*

Chromagram CQT-based

The feature referred to as *chroma_cqt* is another type of chromagram, but created using the [Constant-Q Transform \(CQT\)](#) instead of the [STFT](#). The [CQT](#) have geometrically spaced frequency

bins and the ratios between the center frequencies to the bandwidths are the same [SK10]. Therefore the CQT provides a high frequency resolution for low frequencies and high time resolution for high frequencies.

Figure 2.4 shows a CQT-spectrogram, Figure 2.5 shows the mapping filter, and Figure 2.6 shows the resulting CQT-based chromagram obtained by the dot product of the first and the latter (followed by thresholding and normalization steps).

Figure 2.4: *CQT-spectrogram from a C-major scale sample performed by a piano.*

Figure 2.5: *Filter bank that maps CQT-bins to pitch classes.*

Figure 2.6: *CQT-chromagram from a C-major scale sample performed by a piano.*

Chroma Energy Normalized Statistics

The **Chroma Energy Normalized Statistics (CENS)** [ME11], referred to as *chroma_cens*, is built on top of the previous one. After the *chroma_cqt* is computed the following 5 steps are applied:

1. L^1 -normalization
2. amplitude quantization (using logarithmic compression)
3. smoothing
4. downsampling
5. L^2 -normalization

Figure 2.7: *CENS-chromagram from a C-major scale sample performed by a piano.*

Mel-spectrogram

This feature is a frequency-domain audio representation, but instead of using linear scale as seen in the **STFT**-spectrogram above, it uses a nonlinear one called mel-scale, which was created with the goal to reflect the human perception of pitch intervals, and the exact mapping was achieved in listening experiments [SVN37].

Figure 2.8 shows the filter-bank matrix that map frequencies to the mel-scale, and Figure 2.9 shows the resulting melspectrogram.

Figure 2.8: *Filter bank that maps STFT-bins to Mel-frequency bins.*

Figure 2.9: *Mel-spectrogram from a C-major scale sample performed by a piano.*

Mel-Frequency Cepstral Coefficients

The audio descriptor called [Mel-Frequency Cepstral Coefficients \(MFCC\)](#), widely used in the speech recognition problem [[HCCP06](#), [ISY12](#)], is usually associated with timbre aspects of the songs [[Ell07b](#), [MEK09](#)]. Its definition uses important aspects of the human auditory system [[Pam06](#)]. There are alternative implementations for the [MFCC](#) feature [[GFK05](#)], but the main steps are as follows [[Pam06](#)]:

1. compute the power-spectrum
2. apply a scale change to Mel-frequencies
3. apply another scale change to decibels
4. compute the [Discrete Cosine Transform \(DCT\)](#)

Figure [2.10](#) displays the coefficients for the C major scale performed by a piano whose spectrogram was displayed in Figure [2.1](#).

Figure 2.10: *MFCC extracted from a C-major scale sample performed by a piano.*

Spectral Centroid

The spectral centroid is computed in the frequency-domain, it can be interpreted as the mean of the power-spectrum, and is defined as follows [Ler12]:

$$\text{spectral_centroid}(n) = \frac{\sum_{k=0}^{K/2-1} k |X_n(k)|^2}{\sum_{k=0}^{K/2-1} |X_n(k)|^2},$$

where n is the time frame index.

This feature is usually associated with brightness [TEC01] since more amplitude on high frequencies makes the value of spectral centroid higher. Figure 2.11 shows a clean guitar (blue line) versus a distorted guitar (orange line), and we can observe that the distorted one has larger values for almost all frames. This is expected since the distortion adds lots of harmonic partials leading to higher spectral centroids.

Figure 2.11: *Spectral centroid values extracted from the same guitar sample before and after applying distortion.*

Spectral Bandwidth

The spectral bandwidth is computed in the frequency-domain also, it can be interpreted as the standard deviation of the power-spectrum, and is defined as follows [Ler12]:

$$\text{spectral_bandwidth}(n) = \sqrt{\frac{\sum_{k=0}^{K/2-1} (k - \text{spectral_centroid}(n))^2 |X_n(k)|^2}{\sum_{k=0}^{K/2-1} |X_n(k)|^2}},$$

where n is the time frame index.

This feature is related to timbre characteristics of the audio signal, and can be used as a measure of spectrum spread. It can show if the spectrum has energy concentrated in a narrow band or if it has energy across a larger frequency interval. Figure 2.12 shows the spectral bandwidth for the same two guitar samples we saw before. The addition of distortion (i.e. the addition of harmonic partials) leads to higher spectral bandwidth values.

Figure 2.12: Spectral bandwidth values extracted from the same guitar sample before and after applying distortion.

Spectral Roll-off

The spectral roll-off is defined as the frequency value up to which the accumulated spectrum energy reaches a given percentage. Let this percentage be 85%. If the spectral roll-off is 2000Hz then it means that 85% of the spectrum energy is in the frequencies up to 2kHz. This feature is correlated to the cutting frequency that separates harmonic content from noise [Pee04].

The two guitar samples used before illustrate this feature: the increased energy of the distorted guitar in higher frequencies produces a higher cutting point (i.e., higher roll-off), as seen in Figure 2.13.

Figure 2.13: Spectral roll-off values extracted from the same guitar sample before and after applying distortion.

Spectral Flatness

The spectral flatness, also called tonality coefficient, is another feature computed in the frequency-domain. Dubnov [Dub04] states that it can be used as a measure of randomness present in a signal. So it can be used as a measure of noisiness in the spectrum. It is defined as the ratio of the geometric mean to the arithmetic mean of the energy spectrum value [Pee04]. Figure 2.14 shows the two guitar samples, and we can observe the distorted guitar has highest values, which is consistent to the fact that it has more noise than the clean one.

Figure 2.14: *Spectral flatness values extracted from the same guitar sample before and after applying distortion.*

Spectral Contrast

This feature divides the spectrum in sub-bands and computes the energy ratio between the spectral peaks and the spectral valleys for every sub-band. This ratio is called spectral contrast, and Jiang et al. [JLZ⁺02] state that this feature loosely indicates the harmonic/non-harmonic relative distribution, since the peaks are related to harmonic components, and the valleys with non-harmonic components.

Figure 2.15 displays the spectral contrast values for the two guitar samples discussed above, computed over seven sub-bands.

Figure 2.15: *Spectral contrast values extracted from the same guitar sample before and after applying distortion.*

Tonnetz

The tonnetz, also called harmonic network, is an infinite planar representation that displays the relations of the pitches from the twelve-tone equal temperament. Figure 2.16 shows part of it, and we can observe the basic three types of pitch relations:

1. horizontal lines: perfect fifths
2. upwards diagonals (from bottom-left to top-right nodes): minor thirds
3. downwards diagonals (from top-left to bottom-right nodes): major thirds

This infinite representation can be wrapped around to form an infinite tube in which the line of the fifths becomes a helix on its surface. This helix is known to be part of the spiral array model proposed by Elaine Chew [Che00] and can be seen in Figure 2.17a. For instance, a chord can be represented as a 3-dimensional point inside the tube, as the projection of the pitches in its surface.

A second transformation can be made if we assume enharmonic and octave equivalence. Part of the infinite tube can have both ends joined to compose a hypertorus. Here the circle of fifths goes around its surface three times, as we can see in Figure 2.17b. For instance, a chord can be represented as a 6-dimensional point inside the hypertorus. The 6-tuple can be interpreted as $(x_1, y_1, x_2, y_2, x_3, y_3)$ where:

- (x_1, y_1) is point in the circle of fifths
- (x_2, y_2) is point in the circle of minor thirds

- (x_3, y_3) is point in the circle of major thirds

Figure 2.18 shows these three circles and the tonal centroid that represents the A-major chord.

Finally, every pitch class can be mapped to tonal centroids in this new hypertorus representation, converting 12-bin chromas into a 6-dimensional vector. This defines the *tonnetz* feature that is accordingly associated with melodic and harmonic aspects. Figures 2.19 shows the *tonnetz* extracted from a C-major scale sample.

Figure 2.16: The *tonnetz* infinite planar representation of pitch relations.

(a) The helix of fifths that compose the Chew's spiral array (reproduced from [Che00]).

(b) The hypertorus representation of pitch relations with the helix of fifths going around it (reproduced from [HSG06]).

Figure 2.17

Figure 2.18: The three circles of tone relations and the tonal centroid for the A-major chord (reproduced from [HSG06]).

Figure 2.19: The tonnetz feature extracted from a C-major piano sample.

Root Mean Square

This feature is called **Root Mean Square (RMS)** and it is computed in the time-domain audio representation. It is defined as follows:

$$rms(x) = \sqrt{\frac{1}{N} \times \sum_{i=1}^N x_i^2}$$

RMS is usually associated with dynamics, since it is a display of the signal levels over time. Figure 2.20 shows the **RMS** values of two songs with clear different dynamics. The first song (blue line) is the track “Broken, Beat & Scarred” by the band Metallica, and the second song (orange line) is “Für Elise” performed by the pianist Lang Lang.

Figure 2.20: RMS values extracted from the tracks “Broken, Beat & Scarred” (Metallica) and “Für Elise” (Lang Lang).

Zero Crossing Rate

This feature is computed in the time-domain and is a measure of how many times the audio signal crosses the x-axis. It can be used for several purposes. For instance, if the signal is very simple, such as a sinusoidal wave, the **Zero Crossing Rate (ZCR)** can be a useful measure to help us find the fundamental frequency. Figure 2.21 shows two sinusoids that have 110Hz and 220Hz. Also shows that these signals have ZCR values respectively ≈ 0.00488 and ≈ 0.00976 (notice that the ratio of 1 : 2 is respected).

ZCR can also be used to distinguish periodic and noisy sounds [Pee04]. Figure 2.21 also shows a white noise with its relative ZCR values, and we can see that they are considerably higher than the harmonic ones in the same Figure. ZCR can be used to classify percussive sounds [GPD⁺00] and categorize voiced/unvoiced signals [BKAB10].

Figure 2.21: Zero crossing rate extracted from three basic signals.

Pitch Melodia

Figure 2.22: Fundamental frequencies extracted from the predominant melody of a song using the *Melodia* software.

The audio feature referred to as *pitch_melodia* is composed of the sequence of fundamental frequencies corresponding to the predominant melody in a piece of music. As we can see in Figure 2.22 in some moments the values may be zero. This occurs when no melodic component was detected in that moment (possibly in a silent or noisy part, or in a transition between two notes) [SG12a].

Pitch Contour Segmentation

Figure 2.23: Segmentation of a fundamental frequency sequence, converted to MIDI note numbers.

The feature referred to as *pitch_contour_segmentation* is computed from the feature *pitch_melodia*. The sequence of fundamental frequencies in time is segmented to form a list of notes with their respective pitches and duration values. In addition, pitches are converted from Hertz to [Musical Instrument Digital Interface \(MIDI\)](#) note numbers. As we can see in Figure 2.23 the vertical axis domain is different from the one in Figure 2.22, and the same melody was used to generate both.

Rhythm Pattern

Figure 2.24: Processing pipeline to extract rhythm pattern and related features (reproduced from [PRM02a]).

Pampalk et al. [PRM02b] define the rhythm pattern audio feature computation through the processing steps below (illustrated in Figure 2.24):

1. (for every frame) compute the power-spectrum using Fourier transform;
2. convert frequencies to Bark-scale [ZF13];
3. calculate spectral masking effects [SAH79];
4. transform amplitudes to dB-SPL;
5. determine same amplitude levels with the Phon unit [ZF13];
6. recalculate the amplitudes using the Sone unit [BL81];
7. compute amplitude modulation for each critical band;
8. weight the amplitude modulation coefficients using the fluctuation strength psycho-acoustic model [Fas82];
9. apply gradient and Gaussian filters;
10. calculate the median of every frame result.

This audio feature determines fluctuation patterns for different frequency bands. The result of the steps above can be seen in Figure 2.25 for a simple 4/4 drum sample playing in 120 BPM. We can notice that near 2 Hz we have a column with noticeable amplitude, which is consistent with the track’s tempo. Also there is observable amplitude in columns related to multiples of 2 Hz (1 Hz and 4 Hz, for instance), which is expected regarding the tempo class of 120 BPM.

Figure 2.25: *Rhythm pattern feature extracted for a 120 BPM drum sample.*

Rhythm Histogram

In the processing steps of the previous feature, if we stopped before the fluctuation strength step (see Figure 2.24), we obtain the amplitude modulations that can be aggregated for each critical band resulting in a histogram of modulations. One histogram is computed for each frame of the song, and then the median of them is computed at the end. This is exactly the definition of the current feature called rhythm histogram [LR05], which is illustrated in Figure 2.26 with the same drum sample of the subsection above (and same distinguishable modulation frequencies).

Figure 2.26: *Rhythm histogram feature extracted for a 120 BPM drum sample.*

Temporal Rhythm Histogram

This feature is a statistical summarization of the rhythm histograms computed in time. Rhythm histograms are computed for all frames of a song, and then a set of statistical measures (mean, variance, skewness, kurtosis, median, minimum, maximum) are calculated. The temporal rhythm

histogram is supposed to capture change and variation of rhythmic aspects [Lid07]. Figure 2.27 shows these values for the drum sample whose rhythm histogram is displayed in Figure 2.26.

Figure 2.27: Temporal rhythm histogram feature extracted for a 120 BPM drum sample.

Statistical Spectrum Descriptor

The first six steps of the rhythm pattern processing can be used to define a feature usually called sonogram. For every frame of the song, the algorithm computes the sonogram, and then it calculates 7 statistical measures (mean, variance, skewness, kurtosis, median, minimum, maximum), for each critical band of the sonogram [Lid07]. The final statistical spectrum descriptor is the mean of these statistical vectors over time. An example of this feature is shown in Figure 2.28 extracted from the same drum sample that we have analyzed before.

Figure 2.28: Statistical spectrum descriptor feature extracted for a 120 BPM drum sample.

Temporal Statistical Spectrum Descriptor

This feature is derived from the statistical spectrum descriptor in a similar way as temporal rhythm histogram is derived from the rhythm histogram. The algorithm follows the same steps explained above, however at the end instead of computing the mean of the statistical vectors, it computes the same 7 statistical measures mentioned above to get the final feature. Lidy [Lid07] claims that this feature captures variations on timbre, besides the rhythmic ones. Following our analysis, the temporal statistical spectrum descriptor for the same drum sample is shown in Figure 2.29.

Figure 2.29: Temporal statistical spectrum descriptor feature extracted for a 120 BPM drum sample.

Modulation Variance Descriptor

For every frame of a song, the seven first processing steps of Figure 2.24 are applied. Then the 7 statistical measures are computed for the result vectors. For this feature the critical bands are aggregated, and these measures are intended to resume the modulation frequencies over time. As a final step, the mean of all statistical vectors is taken to conclude the modulation variance descriptor feature. Figure 2.30 shows an example of modulation variance descriptor for the same audio sample as above.

Figure 2.30: *Modulation variance descriptor feature extracted for a 120 BPM drum sample.*

2.2 Feature aggregators

Many features presented above are extracted frame by frame (i.e., they are local features) and, although this potentially reduces data dimension considerably (in comparison to the original audio), their dimension is still very high since it depends on the total length of the song. For example, even a one-dimensional local feature computed using 1024-sample frames without overlapping produces over a thousand values for 30 seconds of audio sampled at 44100 Hz. This figure is in general multiplied by the dimension of the local feature.

In several cases, we want to do a second processing step to decrease the data sizes again. This step consists in aggregating the values of the local features to obtain a descriptor to represent the entire song (global feature). As a bonus, every global feature have the same dimension, which is not true for local features, since different audio files can have different duration values.

In this section we present some methods of local features aggregation used to generate global audio features.

Figure 2.31: Histogram of samples and the Gaussian curve obtained after estimating the parameters μ and σ^2 .

Basic Statistics

The aggregation method we call basic statistics consists in using a normal distribution (see Figure 2.31) to summarize the features frame by frame, that is, the evolution of local features over time. The parameters of a normal distribution are the mean μ and the variance σ^2 .

Let N be the dimension of the local feature for each frame. The global descriptor is a vector composed of the means $[\mu_1, \mu_2, \dots, \mu_N]$ concatenated with the standard deviations $[\sigma_1, \sigma_2, \dots, \sigma_N]$. This version is referred in Tables and Figures as *basic_stats_1*.

We also consider a second aggregation method where we append to the means and standard deviations the minimum and maximum values from the local features. Thus, the global feature vector becomes $[\mu_1, \dots, \mu_N, \sigma_1, \dots, \sigma_N, \min_1, \dots, \min_N, \max_1, \dots, \max_N]$, and is referred to as *basic_stats_2*.

Difference Statistics

This method of aggregation is quite similar to the previous one, but adds to the global feature information about the local feature's discrete difference, defined as $\text{diff}[i] = \text{feature}[i + 1] - \text{feature}[i]$, and illustrated in Figure 2.32.

Figure 2.32: The discrete difference of the *chroma_stft* displayed in Figure 2.3.

Here we define also two alternative aggregation methods. The first one, referred to as *diff_stats_1*, is defined as $[\mu_1, \dots, \mu_N, \sigma_1, \dots, \sigma_N]$ concatenated with $[\mu_{diff_1}, \dots, \mu_{diff_N}, \sigma_{diff_1}, \dots, \sigma_{diff_N}]$ (the means and standard deviations of the feature's difference). The second one, referred to as *diff_stats_2*, is the *diff_stats_1* vector concatenated with $[\min_1, \dots, \min_N, \max_1, \dots, \max_N]$ and $[\min_{diff_1}, \dots, \min_{diff_N}, \max_{diff_1}, \dots, \max_{diff_N}]$ (the minimum and maximum values of the feature's difference). Therefore, the difference statistics vectors have double the dimension of the basic statistics ones.

Statistical Summarization

This is the third aggregation method that uses a single Gaussian as the statistical model. The global feature is composed of N means, N variances and $\frac{N(N-1)}{2}$ covariances, having the dimension $2N + \frac{N(N-1)}{2}$. The number of covariances is $\frac{N(N-1)}{2}$, because the covariance matrix is symmetric, and we can only use values below the main diagonal. This feature is referred in this text as *statistical_summarization*.

Gaussian Mixture Model

When the samples are organized in sub-populations, it is not enough to represent them with only one normal distribution. In this case, we can use the [Gaussian Mixture Model \(GMM\)](#) that considers K components to represent the data (see Figure 2.33).

Consider that the local features have the format (M, N) , where M is the number of frames and N is the dimension of each local feature. After the adjustment process by the model, the global feature is represented by an array of means in the (K, N) format, a covariance tensor in the format (K, N, N) and a vector of K size weights (all flattened to form a vector).

Figure 2.33: Histogram of samples and the estimated two-component GMM.

Vector Quantization

In this aggregation technique we start gathering all local features from every song in the dataset. Then, we use a clustering algorithm (in our project we use k-means) to partition these samples into separate K groups. Each group is represented by their centroid. The set of all centroids is called dictionary. Then we scan each song and count for every local feature which is the closest centroid. The global feature that represents the whole song is the histogram of centroid occurrences (i.e. the histogram of the dictionary items).

Papers that present this technique use small dictionary sizes (for instance, 8) and, although the processing takes more time and has a higher demand for memory (all songs are processed together), the global descriptor has a very small dimension compared to the local one.

Figure 2.34a shows 10 fictitious songs each one with 50 frames (so we have 500 sample points in the graph) and a fictitious feature whose dimension is 2. The samples of one song are highlighted in red, and we can observe that a subset of these points is closer to the first centroid, and the rest is closer to the second centroid. Figure 2.34b displays the final histogram for this song: the local features from 13 frames were closer to centroid 1, and 37 to centroid 2. The global descriptor is the vector [13, 37].

(a) Example with two sample populations and the respective centroids (b) An example histogram of count-computed by the k-means algorithm, and the frames from one song ing the closest centroids to the samples highlighted in red color.

Figure 2.34

Markov Chains

Audio signals are time series, that is, the occurrence of a sample is not independent from previous samples. This remains true after extracting the local descriptors, so it is desirable to use some aggregation method that considers the order of the descriptors.

Note that in the previous techniques, any global feature is the same if we perform a random permutation of the respective local features. For instance, the means and variances of a data set remain the same regardless of the order in which they are processed; the histogram of dictionary items remains the same regardless of the order in which the samples are counted.

With the purpose of not ignoring the order in which local features temporally occur, an alternative is to use Markov chains. They have states that represent values and edges that represent transitions between states, each edge associated with a probability of transition between states (as we can see in Figure 2.35).

Figure 2.35: Markov chain built from a simple melody.

Octave Abstraction

This method is designed for pitch vectors that can be obtained by discarding the duration values from the Pitch Contour Segmentation feature (as displayed in Figure 2.36). We can apply some abstractions to this list. The first, which defines the current technique, is to take only the chromas instead of the pitches [SSG13b].

The result can be seen in Figure 2.37, and the formula that defines it from the original list of pitches is:

$$\text{octave_abstraction}(i) = \text{pitch}(i) \% 12$$

[60, 60, 64, 67, 64, 60, 62, 62, 62, 59, 62, 62, 59, 59, 55, 60, 60, 64, 67, 64]

Figure 2.36: MIDI note number sequence obtained discarding the duration values from the Pitch Contour Segmentation feature.

[0, 0, 4, 7, 4, 0, 2, 2, 2, 11, 2, 2, 11, 11, 7, 0, 0, 4, 7, 4]

Figure 2.37: Octave abstraction to a melodic line.

Interval Abstraction

This method is also designed for the sequence of MIDI note numbers. It is called interval abstraction, considers the finite difference of the melodic line, and is defined according to the following formula [SSG13b]:

$$\text{interval_abstraction}(i) = \text{pitch}(i + 1) - \text{pitch}(i)$$

The outcome for the same melodic sequence presented in Figure 2.36 above can be seen in Figure 2.38.

$[0, 4, 3, -3, -4, 2, 0, 0, -3, 3, 0, -3, 0, -4, 5, 0, 4, 3, -3]$

Figure 2.38: *Interval abstraction to a melodic line.*

Pitch Contour: 3 levels

This technique is also constructed from a sequence of pitches. In this case, we have another interval abstraction, but instead of computing the difference, we only check if the values go up ('u'), down ('d'), or repeat ('r') [GLSC95]. The formula that defines it is:

$$p_{3_levels}(i) = \begin{cases} 'u', & \text{pitch}(i) > \text{pitch}(i-1) \\ 'd', & \text{pitch}(i) < \text{pitch}(i-1) \\ 'r', & \text{otherwise.} \end{cases}$$

The result for the melodic sequence from the previous examples can be seen in Figure 2.39.

$['r', 'u', 'u', 'd', 'd', 'u', 'r', 'r', 'd', 'u', 'r', 'd', 'r', 'd', 'u', 'r', 'u', 'u', 'd']$

Figure 2.39: *3-level pitch contour abstraction to a melodic line.*

Pitch Contour: 5 levels

This method is very similar to the previous one, but considers 5 levels: up ('u'), up a lot ('U'), down ('d'), down a lot ('D'), and repeat ('r') [RH06b]. Its definition is as follows:

$$p_{5_levels}(i) = \begin{cases} 'U', & \text{pitch}(i) > \text{pitch}(i-2) \\ 'D', & \text{pitch}(i) < \text{pitch}(i-2) \\ \begin{cases} 'u', & \text{pitch}(i) > \text{pitch}(i-1) \\ 'd', & \text{pitch}(i) < \text{pitch}(i-1) \\ 'r', & \text{pitch}(i) = \text{pitch}(i-1) \end{cases} & , \text{pitch}(i) = \text{pitch}(i-2) \end{cases}$$

The values obtained from the melody in Figure 2.36 are shown in Figure 2.40.

$['U', 'U', 'd', 'D', 'D', 'U', 'r', 'D', 'u', 'U', 'D', 'D', 'D', 'U', 'U', 'U', 'U', 'd']$

Figure 2.40: *5-level pitch contour abstraction to a melodic line.*

2.3 Distance measures

The next step, after selecting an audio descriptor and a feature aggregator, is to decide how to compare global features of two songs. The computation of the similarity between two songs is based on the distance between them. In this section we present all the distance measurements we use.

(a) Manhattan distances to $(0,0)$ computed for values in a discrete rectangle in $\mathbb{R}^2$ for illustration. (b) Euclidean distances to $(0,0)$ computed for values in a discrete rectangle in $\mathbb{R}^2$ for illustration.

(c) Chebyshev distances to $(0,0)$ computed for values in a discrete rectangle in $\mathbb{R}^2$ for illustration. (d) Cosine distances to $(1,1)$ computed for values in a discrete rectangle in $\mathbb{R}^2$ for illustration.

Figure 2.41

Manhattan distance

The first distance function is the Manhattan that computes the distance between two elements of a vector space ($\mathbb{R}^n$ in our case) according to the following formula:

$$\text{manhattan_distance}(u, v) = \sum_{i=1}^n |u_i - v_i|$$

Euclidean distance

The Euclidean distance is also computed in the $\mathbb{R}^n$ vector space and follows the formula below:

$$euclidean_distance(u, v) = \sqrt{\sum_{i=1}^n (u_i - v_i)^2}$$

Chebyshev distance

The Chebyshev distance is computed between two vectors in $\mathbb{R}^n$ according to the following formula:

$$chebyshev_distance(u, v) = \max(|u_i - v_i|)$$

Cosine distance

The cosine distance is defined for non-zero vectors in $\mathbb{R}^n$ space as the formula below:

$$cosine_distance(u, v) = 1 - \frac{u \cdot v}{\|u\| \|v\|}$$

LCS-based distance

The algorithm that computes the **Longest Common Subsequence (LCS)** can be used to obtain a distance between two sequences of symbols. This dynamic programming algorithm handles additions, deletions and substitutions, and returns the size of the largest common subsequence. This is actually a value of similarity between the two sequences. To obtain a distance measure one possibility is to use the ratio between the **LCS**-length and the length of the longest sequence, as defined by the following formula:

$$lcs_distance(u, v) = 1 - \frac{lcs_length(u, v)}{\max(|u|, |v|)}$$

Alternatively, this ratio can be computed using the length of the shortest subsequence being compared, and the mean length of both sequences. Figure 2.42 shows the comparison between two sequences of length 9. The length of the longest common subsequence is 7. So the distance is $1 - 7/9 \approx 0.222$.

Figure 2.42: An example of the longest common subsequence computation.

Levenshtein's distance

Levenshtein's distance, also known as edit distance, is defined between two sequences of symbols and provides us with the number of insertion, deletion or substitution operations necessary to transform one sequence into another. It is defined according to the formula below:

$$levenshtein_distance_{u,v}(i, j) = \begin{cases} \max(i, j), & \text{if } \min(i, j) = 0 \\ \min \begin{cases} levenshtein_distance_{u,v}(i-1, j) + 1 \\ levenshtein_distance_{u,v}(i, j-1) + 1 \\ levenshtein_distance_{u,v}(i-1, j-1) + I(u_i, v_j) \end{cases} & , \text{otherwise.} \end{cases}$$

where $I(x, y) = 0$ if $x = y$ and $I(x, y) = 1$ if $x \neq y$.

Here the ratio between the Levenshtein distance and the minimum, maximum, and mean of the sequences' lengths is also computed. Figure 2.43 gives an example of two sequences of size 9. The edit distance is 3, and the final distance value is $3/9 \approx 0.333$.

Figure 2.43: An example of the edit distance computation.

Kullback-Leibler distance

The **Kullback-Leibler (KL)** divergence [KL51], also known as relative entropy, gives us a measure of how much two probability distributions differ from each other. If P and Q are two continuous distributions, the **KL**-divergence is defined as:

$$kl_divergence(P, Q) = \int_{-\infty}^{\infty} p(x) \log\left(\frac{p(x)}{q(x)}\right) dx$$

If P and Q are two discrete distributions, the **KL**-divergence is defined as:

$$kl_divergence(P, Q) = \sum_i P(i) \log\left(\frac{P(i)}{Q(i)}\right)$$

However, one of our premises is that the distance functions should be symmetrical. Since this is not true for a divergence, a distance measure can be defined according to the formula below [KS16]:

$$kl_distance(P, Q) = \frac{1}{2}(kl_divergence(P, Q) + kl_divergence(Q, P))$$

Figure 2.44 shows how this distance behaves by comparing several distributions with a base distribution (with mean equals 0 and standard deviation equals 1). The parameters of these distributions are shown on the axes, the horizontal axis represents the means and the vertical one the standard deviations.

Note that the distance increases as the mean increases, and also when the standard deviation increases. However there is a slight inequality in this growth. The distance is more sensitive to the variation of the standard deviation than to the mean.

Figure 2.44: *Kullback-Leibler distance calculated for pairs of Gaussian distributions.*

Earth Mover's distance

The [Earth Mover's Distance \(EMD\)](#), also called Wasserstein distance, is defined between two distributions of probability. It has this name as an analogy where each distribution is a mound of land and the metric is related to the minimum cost of transforming one mound into another, considering the distance and also the amount of earth to be transported between them.

To illustrate how this distance behaves, we computed the [EMD](#) for several Gaussian distributions against one fixed distribution (with mean equals 0 and standard deviation equals 1). The results are shown in [Figure 2.45](#).

Figure 2.45: *EMD calculated for pairs of Gaussian distributions.*

Monte Carlo distance

When comparing two distributions we can determine how distant they are by taking samples from the first one and computing the probability that these samples were generated by the second.

This method known as Monte Carlo sampling can be used to create a measure of distance, according to the following formula [AP04]:

$$\begin{aligned} monte_carlo_distance(P, Q) = & \sum_{i=1}^s \log p(S_i^P|P) + \sum_{i=1}^s \log p(S_i^Q|Q) \\ & - \sum_{i=1}^s \log p(S_i^P|Q) - \sum_{i=1}^s \log p(S_i^Q|P), \end{aligned}$$

where P, Q are the probability distributions, S_i^A is the i -th sample of A , and $p(S_i^A|B)$ is the probability that the i -th sample of A is in B .

Figure 2.46 shows the values of Monte Carlo distances calculated for the same pairs of normal distributions we considered in the two previous distance measures.

Figure 2.46: Monte carlo distance calculated for pairs of Gaussian distributions.

2.4 Music similarity quality measures

After choosing an audio feature, an aggregation technique and a distance measure (that is, a triplet $\{extractor, aggregator, distance\}$ which defines a music similarity model), we would like to know the quality of this model on estimating similarity values for a dataset. In this section we will look at two representations commonly seen in the literature, and propose a new one.

Similarity matrix

The most popular way found in the literature to obtain a representation of the music similarity model quality is the similarity matrix. Its creation consists in computing the similarity of all possible music pairs in the dataset. The i, j position of this matrix contains the similarity between the i -th and the j -th songs. It can be defined from a distance measure according to the following formula (where $\hat{dist}$ is normalized between 0 and 1):

$$sim(t_i, t_j) = 1 - \hat{dist}(t_i, t_j)$$

As we can see in Figure 2.47 the matrix main diagonal has the highest values (because the songs have maximum similarity with themselves) and we can also observe some darker and lighter regions. The darker regions show a subset of the data with high intra-similarity. In Figure 2.47, for example,

we were able to identify darker square regions (4×4) related to songs of a class with high internal similarity. The lighter colored regions represent a lower inter-similarity. Again, in Figure 2.47 we can identify a cross-shaped region showing a low external similarity of the second class.

Figure 2.47: Similarity matrix computed for a toy dataset with 20 tracks divided in 5 classes (4 tracks per class).

Intra-inter-class similarity ratio

We can also compute more succinct values to measure a music similarity model's quality. The authors of the book entitled "Music Similarity and Retrieval" [KS16] define them in terms of tracks' genres in order to compare the intra-genre similarity with the inter-genre similarity (for all genres). We are changing their terminology from "genre" to "class" to address more generic cases. For every class annotated in the dataset we compute the intra-inter-class similarity ratio from the similarity matrix according to the following formula:

$$iicsr(c) = \frac{\sum_{t_1 \in T_c} \sum_{t_2 \in T_c, t_1 \neq t_2} sim(t_1, t_2)}{\frac{(|T_c|^2 + |T_c|)}{\sum_{t_1 \in T_c} \sum_{t_2 \in T_{C \setminus c}} sim(t_1, t_2)}},$$

where T_c is the set of all tracks in the class c and $T_{C \setminus c}$ is the set of all tracks not in the class c .

This measure quantifies the similarity between tracks in the same class (weighted by the number of tracks in the class) over the similarity between tracks in that class and tracks in other classes (weighted by the number of tracks in the other classes). If this ratio is greater than 1, then the intra-class similarity is greater than the inter-class, and this means that the model is able to better separate tracks from that specific class.

Weighted mean intra-inter-class similarity ratio

Since the intra-inter-class similarity ratio is computed for every class we still have a group of values, which makes the task of comparing two similarity models still not straightforward (this was our goal when decreasing the number of values to be compared from n_{tracks}^2 of the similarity matrix to $n_{classes}$). We can define an even leaner quality measure which is the mean of all intra-inter-class similarity ratios weighted by the size of the classes:

$$iicsr_{weighted_mean} = \frac{1}{\sum_{c \in C} |T_c|} \sum_{c \in C} iicsr(c) \times |T_c|$$

Chapter 3

Cover Song Identification

A cover song consists in an alternative recording of another song that is usually referred as the original one. The term version can also be used in a similar way. The versions of a song can be different from the original one in several musical aspects. Serrà et al. [SGH10] make an extensive list of these variant characteristics.

Considering the perceptual properties of the sound as pitch, duration, intensity and timbre, every single one of the related musical attributes (e.g., melody, harmony, rhythm, tempo, dynamics, timbre) can change from one version to the other.

For instance, timbre can vary between versions. From countless scenarios, timbre can change due to differences in mixing or mastering, and also due to different instrumentations on recordings of the same songs. Figure 3.1 illustrates three releases of the album *Let It Be* by The Beatles. Figure 3.1a illustrates the original album cover as released on 1970, Figure 3.1b illustrates the 2012 stereo remastered version, and Figure 3.1c illustrates the cover of the alternative mixing released on 2003 in which several orchestral and other types of embellishments introduced by the producer Phil Spector were removed, among other differences.

Figure 3.1: *Three distinct releases of the album Let It Be by The Beatles.*

Distinct timbre can be observed in live recordings, even if performed by the same band, and even if the same instruments were used, as a result of the recording environment. Figure 3.2 illustrates four versions of the album *The Wall*: Figure 3.2a contains the original studio one by Pink Floyd, Figure 3.2b displays a live version recorded on 1980-81 also by Pink Floyd, and Figures 3.2c and 3.2d illustrate two live recordings performed by Pink Floyd's bassist Roger Waters, recorded on 1990 and 2012 respectively, with different personnel and equipment.

Figure 3.2: Four distinct releases containing songs from the album *The Wall* by Pink Floyd.

Versions can have distinct tempi also. This can happen for several reasons, but usually the tempo is changed for expressiveness and contextual purposes [SGH10]. The song *All Along the Watchtower*, performed by Jimi Hendrix (as illustrated in Figure 3.3b), has the tempo of 116BPM (according to the website Note Discover¹), while the original version, recorded by Bob Dylan (as illustrated in Figure 3.3a), has the tempo of 130BPM (also according to Note Discover²).

Figure 3.3: Labels from two singles of *All Along the Watchtower* originally recorded by Bob Dylan (a), and covered by Jimi Hendrix (b).

Rhythm is composed of several aspects besides tempo, and all of them can change between versions. For instance, distinct versions can have completely different time signatures. The song *With a Little Help from My Friends* was originally recorded by The Beatles (as displayed in Figure 3.4a) in a $\frac{4}{4}$ beat (according to the sheet music available on Music Notes³), while the version of it performed by Joe Cocker (as illustrated in Figure 3.4b) was recorded in a $\frac{12}{8}$ beat (according to the Music Notes' sheet music⁴).

Figure 3.4: Labels from two singles of *With a Little Help from My Friends* originally recorded by The Beatles (a), and covered by Joe Cocker (b).

As we can observe in the literature (and illustrate in the following quotes), tonal aspects tend to be the least variant factor between version songs.

¹<https://www.notediscover.com/song/jimi-hendrix-all-along-the-watchtower>

²<https://www.notediscover.com/song/bob-dylan-all-along-the-watchtower>

³<https://www.musicnotes.com/sheetmusic/mtd.asp?ppn=MN0053730>

⁴<https://www.musicnotes.com/sheetmusic/mtd.asp?ppn=MN0054613>

“In general, we can assume that different versions of the same piece mostly preserve the main melodic line and/or the harmonic progression, regardless of its main key. For this reason, tonal or harmonic content is a mid-level characteristic that should be considered to robustly identify covers.”

Joan Serra et al. [SGH10]

“Systems for the automatic detection of versions exploit musical facets which remain mostly unchanged across different renditions, primarily the harmonic (or tonal) progression.”

Justin Salamon et al. [SSG12]

“What remains almost invariable among the various cover versions are harmonic progressions and melody evolution, which form the basis of the most existing CSI descriptor extraction algorithms.”

Ning Chen et al. [CLX17]

However, we still need to face a few challenges regarding tonal information. For instance, the key can be different. It can change to adjust to the singer vocal range or for aesthetics reasons [SGH10]. The versions of All Along the Watchtower, previously referenced, were recorded in different keys (the original was in A Minor, and the version was in C# Minor).

Harmony can also vary between versions. The chord progression can be altered in several ways: chords can be added, removed or altered (adding and removing intervals). For instance, George Benson recorded an album called The Other Side of Abbey Road where he recorded several Beatles' songs. His version of Here Comes the Sun is completely re-harmonized.

Still regarding tonal changes, even though it is very rare, melody is subject to change as well. It can occur with the use of vocal ornaments, improvisation, among other reasons. Frank Zappa's live cover of Sunshine of Your Love (originally by The Cream) is a radically different rendition of it, where one can identify the main theme of the song, but the overall main melody is extinguished.

Other aspects can change such as dynamics (e.g., the overly compressed metal recording done by Children of Bodom of the song Oops I Did It Again! by Britney Spears), lyrics (e.g., the Brazilian singer Zé Ramalho who recorded a Portuguese translated version from Knockin' on Heaven's Door by Bob Dylan, called Bate-Bate-Bate na Porta do Céu), noise level (e.g., the early Beatles live recordings with quite loud audience talking and screaming), and also the structure, which is particularly challenging since bands can decide to add a non-pre-existing introduction, or to repeat the chorus, or even completely change the order of the original sections.

3.1 Cover song identification

The **Cover Song Identification (CSI)** problem, that can also be called **Cover Song Detection (CSD)** [EC07, RE10, LS10] or **Cover Song Retrieval (CSR)** [LH06, Bel07, SZA09], is basically the task of identifying songs that are versions of each other in a group of songs. Ravuri and Ellis [RE10] define it as retrieving n cover songs of a query track from a set of m songs.

Serra et al. [SGH10] state that the standard approach is to use music similarity techniques since the cover songs share some music elements between them, and this should be explored. Furthermore, the use of tonal similarity is considered very robust to identify covers [SGH10, SSG12, CLX17], and it is the most common approach in the literature.

3.1.1 CSI methods that use tonal features

Gómez et al. [GHO06] present a technique for the CSI problem that uses tonal descriptors. More specifically, they use the **Harmonic Pitch Class Profile (HPCP)** feature, which is very similar

to chromagrams (as seen in Section 2.1). Among the differences between them we have: **HPCP** is usually computed with higher interval resolution (e.g., 36-bins [SGHS08] or 120-bins [GHO06]) and for a narrower frequency band (e.g., 50-5000Hz [SSG12] or 100-5000Hz [Góm06]).

They compute **HPCPs** for every frame of a song, and then they perform two distinct processing pipelines. The first one estimates the song's key and converts the **HPCP** vectors into **Transposed Harmonic Pitch Class Profile (THPCP)** vectors, which is a transposition-invariant feature [GHO06]. The second pipeline performs a structural analysis using an improved version of the algorithm introduced by Goto [Got03].

This analysis returns segmentation profiles of the songs, and then two segments are selected for each song as their music summaries using the following two criteria: the segment should repeat at least once in the song, and the segment's group should retain the majority of the song's duration.

At the end of these two pipelines, that are illustrated in Figure 3.5a, they obtain a **THPCP** for the whole song, and two **HPCP** vectors (one for each selected segment). These feature vectors are used in two different versions: the instantaneous evolution and their global average.

When comparing two songs, the similarity values are computed for both features extracted from the entire songs, and from the two segments of each song. The global averages are compared using Pearson's correlation coefficients, and the instantaneous evolutions are compared using a **Dynamic Time Warping (DTW)** algorithm. In the segment's comparison case, they obtain four values (as shown in Figure 3.5b) and the final similarity is the highest one.

Figure 3.5: Feature extraction pipeline and segments comparison scheme by Gómez et al. [GHO06].

Jensen et al. [JCEJ08] propose a system for the **CSI** problem that is invariant to different instrumentation, timing, tempo and transposition. They start the feature extraction process computing 12-bin chromagrams for every song, following the implementation introduced by Ellis and Poliner [EP07], which is invariant to instrumentation.

$$C = \begin{bmatrix} c_1(1) & \dots & c_1(N) \\ \vdots & & \vdots \\ c_{12}(1) & \dots & c_{12}(N) \end{bmatrix}$$

where c_i is the i -th row of the chromagram related to the i -th pitch class.

Next, they apply an element-wise logarithm scaling on the chromagram matrices based on the argument that this will increase the quality of the results, because the human perception of loudness can be roughly comparable to log-scale.

$$C_{log} = \begin{bmatrix} \log(1 + \frac{c_1(1)}{\delta}) & \dots & \log(1 + \frac{c_1(N)}{\delta}) \\ \vdots & & \vdots \\ \log(1 + \frac{c_{12}(1)}{\delta}) & \dots & \log(1 + \frac{c_{12}(N)}{\delta}) \end{bmatrix}$$

where δ is a small constant

Then, they compute the power spectrum of each line of the chromagram to prevent time alignment problems allowing invariance to time shifts or tempo changes.

$$C_{pwr} = \begin{bmatrix} |\mathcal{F}(c_1^{log})|^2 \\ \vdots \\ |\mathcal{F}(c_{12}^{log})|^2 \end{bmatrix}$$

where $\mathcal{F}$ is the Fourier transform.

After that, they sample the rows of C_{pwr} using a bank with 25 logarithmically spaced filters with 50% overlapping, as displayed in Figure 3.6. This is done to further increase tolerance to timing variations.

Figure 3.6: Filter bank applied by Jensen et al. [JCEJ08] in order to increase timing invariance.

Finally, the similarity between two songs' features is computed using the Frobenius distance. First they normalize the feature matrices, then they select the minimum Frobenius distance when comparing one matrix to all 12 possible transpositions of the other one, in order to achieve transposition invariance. Later, they also shifted the matrices up to 2 columns to increase the tolerance to time deviations. The shift that led to the smallest Frobenius distance is the final distance measure between the two songs.

3.1.2 CSI methods that use symbolic sequences

Some other approaches try to extract the main melody from the audio files, and then compare sequences in the symbolic-domain. Tsai et al. [TYW⁺05] present a technique to extract the main melody of non-vocal segments of the songs. This is done under the argument that accompaniments can vary substantially between versions, and if non-vocal segments are passed to the melody extraction algorithm, it can lead to spurious melody sequences that are not related to singing voice.

In order to remove the non-vocal segments cepstral-based feature vectors are extracted from the segments, and two different **Gaussian Mixture Model (GMM)**s are used: one to model the vocal segments; the other to model the non-vocal segments. The training is performed with manually

annotated samples. Then, when the query song is processed, features are extracted from it and likelihoods are computed from both [GMMs](#) in order to classify each segment as vocal or non-vocal.

The process of extracting the main melody follows several processing steps that can be consulted in the original paper [\[TYW⁺05\]](#). The signal is fragmented, windowed, then for every frame the spectrum is computed and spectral intensity analysis is performed. Since the fundamental frequency can not be located at the spectral maxima, [Sub-Harmonic Summation \(SHS\)](#) [\[PG79\]](#) is applied.

Another issue that has to be faced is when the detected note number is related to the accompaniment. So, under the assumption that the accompaniment is often repeated in neighboring segments, a method to identify which notes are more likely to be produced by instruments is applied, in order to mitigate the impact of partials that belong to the accompaniment.

As post-processing steps short- and long-term constraints are applied. First a median filter is used to remove jitters, then the octaves of outlier notes are corrected, based on the premise that the range of singing voices is somewhat narrow.

Finally, the similarity computation between note sequences is done using a [DTW](#) algorithm to find the temporal alignment between them. This algorithm computes a matrix D that contains the distances between the note sequences. The similarity of two note sequences is computed as follows:

$$S(q, u) = \begin{cases} \max_{\frac{T}{2} \leq l \leq \min(2T, L)} (\frac{1}{D(T, l)}), & \text{if } L \geq \frac{T}{2} \\ \infty, & \text{if } L < \frac{T}{2} \end{cases}$$

where $T = |q|$, $L = |u|$, and D is the matrix computed by the [DTW](#) algorithm.

Finally, in order to handle different transpositions the previous formula is computed to transposed versions of one of the sequences as follows:

$$S_{final}(q, u) = \max_{-K \leq k \leq +K} S(q^{(k)}, u)$$

where K is the maximum allowed transposition value in semitones, $q^{(i)}$ is the i -th transposition of the sequence q .

Marolt [\[Mar06\]](#) presents a melody-based approach to the [CSI](#) problem that handles variations on rhythm and structure. It starts using a melody extraction algorithm proposed by Marolt in a past work [\[Mar05\]](#). This algorithm returns a set of melodic fragments, each one with start and end times, loudness and pitch variations in that time interval. The melodic representations have their frequency mapped to 24 values per octave thus alleviating the effects of pitch variations (such as in vibratos). Octave abstraction is also applied, mapping every frequency values to one octave.

In order to be a rhythmic invariant technique, a beat tracker is used and an average filter is applied to the melody representation (6 frames for every beat). Beyond that, to be invariant to structure variations, a [Self-Similarity Matrix \(SSM\)](#) of the beat-synchronous melody representations is computed using cosine distance, followed by several post-processing steps.

The [SSMs](#) helps the author to look for melodic patterns, which are melody fragments that appear more than once in the song. These patterns are selected using a greedy algorithm that locates the most repeated fragment and its duplicates, removes them all from the [SSM](#), and then redo these two steps until 90% of the [SSM](#) is gone.

When comparing two songs, the algorithm computes correlations of the first song to circular-shifted versions of the second one to be able to find the best transposition. Then all patterns from both songs are compared using cosine similarity. When comparing two patterns, since they can be of different sizes (also not temporally aligned), the similarities of the largest one versus shifted versions of the smallest one are all computed. Then, the final similarity of a pair of patterns is the highest computed one. The final similarity value between the two songs is the mean of the best n matching patterns similarity values (n empirically set to 2).

3.1.3 CSI methods that use fusion methods

One important technique that is applied in the CSI problem is the [Similarity Network Fusion \(SNF\)](#) proposed by Wang et al. [[WMD⁺14](#)]. Let us consider one dataset with n samples and m different similarity measures. We can represent a similarity network as a graph $G = (V, E)$, where V is the set of the samples $x_1, x_2, \dots, x_n$, and E is the set of the edges which are weighted by how similar the samples are.

For one fixed distance measure represented by the function ρ , the authors define the exponential kernel W as follows:

$$W(i, j) = \exp\left(-\frac{\rho^2(x_i, x_j)}{\mu \epsilon_{i,j}}\right) \quad (3.1)$$

where $\begin{cases} \epsilon_{i,j} = \frac{\text{mean}(\rho(x_i, N_i)), \text{mean}(\rho(x_j, N_j)), \rho(x_i, x_j)}{3} \\ \text{mean}(\rho(x_i, N_i)) \text{ is the average value of the distances between } x_i \text{ and its neighbors} \\ N_i \text{ represents the set of the neighbors of } x_i \text{ (including } x_i) \\ \mu \text{ is a hyperparameter that can be empirically set } (\mu \in [0.3, 0.8]) \end{cases}$

Then they define the transition matrix P as we can see below:

$$P(i, j) = \begin{cases} \frac{1}{2} \frac{W(i,j)}{\sum_{k \neq i} W(i,k)}, & \text{if } j \neq i \\ \frac{1}{2}, & \text{otherwise} \end{cases} \quad (3.2)$$

Next, they define a [K-Nearest Neighbors \(KNN\)](#) version of P with this formula:

$$S(i, j) = \begin{cases} \frac{W(i,j)}{\sum_{k \in N_i} W(i,k)}, & \text{if } j \in N_i \\ 0, & \text{otherwise} \end{cases} \quad (3.3)$$

We should note that P stores the similarities of each sample to all others, while S only stores the K highest similarity values of each sample. Lastly, the final fused network using m different measures is defined as:

$$P^{(v)} = S^{(v)} \times \left(\frac{\sum_{k \neq v} P^{(k)}}{m-1} \right) \times (S^{(v)})^T \quad (3.4)$$

for $v = 1, 2, \dots, m$

Tralie [[Tra17](#)] proposes a CSI system that uses the SNF method in order to combine the strengths of each considered feature. It starts with the extraction of three different features. The first one is [HPCP](#) which is followed by the computation of a stacked delay embedding using delay coordinates (as done by Joan Serra et al. [[SSA09](#)]). Also [Optimal Transposition Index \(OTI\)](#) is applied to achieve transposition invariance.

Then [Mel-Frequency Cepstral Coefficients \(MFCC\)](#) features are computed for every beat-synchronous block (20 beats per block). These features are then exponentially scaled, interpolated (400 MFCCs per block), and normalized using the technique by Tralie and Bendich [[TB15](#)]. As the third feature, a list of [SSMs](#) is computed between every block of the song being analysed (instead of a unique SSM for the whole song). Euclidean distances are calculated for all windows inside each block, taking window length of 0.5 second and hop size of 512 samples.

After these three features are extracted, three [Cross-Similarity Matrices \(CSMs\)](#) are computed using the feature's sequences from the pair of songs. The CSM of the HPCP is built using cosine distance; the CSMs of MFCC and MFCC SSMs are built using Euclidean distance. Then all CSM are converted into binary matrices, and the Smith Waterman algorithm is applied to them in order to find the best local alignments.

Additionally to using the isolated features, the application of SNF, the method proposed by Wang et al. [[WMD⁺14](#)] that was presented before, is utilized. Both early and late fusions are

applied, as can be seen in Figure 3.7.

Figure 3.7: The complete processing diagram of the system proposed by Tralie [Tra17].

The early fusion is performed at feature level before calling the Smith Waterman algorithm. For every type of feature - **HPCP**, **MFCC**, **MFCC SSMs** - the algorithm builds a matrix called “parent **SSM**”. As displayed in Figure 3.8 we have four distinct regions: the **SSM** of the song A (top-left), the **SSM** of the song B (bottom-right), the **CSM** of the songs A and B (top-right), and the **CSM** of the songs B and A (bottom-left). Since the values on the **SSM** regions are much higher than the ones on the **CSM** regions, a normalization step that made the values to be scaled properly is performed. Then these “parent **SSMs**” are fused using the **SNF**, and the output of it is passed as an argument to the Smith Waterman algorithm.

Figure 3.8: The parent Self-Similarity Matrix built by Tralie [Tra17] as input to the Similarity Network Fusion algorithm.

The late fusion step is much simpler. The **SNF** technique is applied to fuse score matrices between all pairs of songs for the feature set. Since the **CSMs** are already computed for each feature, element-wise inverse mapping is applied, and then the fused transition matrix is obtained from the **SNF**, which is used to compute the final score.

Chen et al. [CLX18] also use **SNF** to the **CSI** problem. They use only one type of feature - 12-bin **HPCP** - extracted for every 464ms frame, in the 5Hz-5000Hz frequency range, with loudness normalization, tuning estimation, and spectral whitening.

For the similarity computations they use two functions. The first one is Q_{max} , created by Serrà et al. [SSA09] and the second one, called D_{max} , is a modification of Q_{max} . The only difference between them is the considered alignment constraints, as can be seen in Figure 3.9.

Figure 3.9: The considered alignment constraints used by (a) Q_{max} and (b) D_{max} (reproduced from [CLX18]).

After they obtain two similarity matrices (one for each similarity function above), they use SNF to fuse them, as we saw earlier on this section. The complete process is illustrated in Figure 3.10.

Figure 3.10: The complete system diagram as proposed by Chen et al. [CLX18].

3.1.4 Cover song identification quality measures

Figure 3.11: An illustration of one column from the similarity matrix before and after being ordered, and how to determine the rank of the first retrieved cover of the column's correspondent song.

Mean Rank (MR)

The **Mean Rank (MR)** can be used as a measure of the quality of a **CSI** system given a dataset. We can interpret it as the expected position where the first cover will appear in the result list when querying a song. It is broadly used in the literature [Tra17, SHD19] and it is defined from the similarity matrix $S \in \mathbb{R}^{N \times N}$ as follows:

1. Sort in descending order every column (song) $j = 1, 2, \dots, N$ of the similarity matrix S , producing a matrix K where $K_{i,j}$ is the index of the i -th most similar song to j . In other words, the sorted values of the j -th column of S are

$$S_{K_{1,j},j} \geq S_{K_{2,j},j} \geq \dots S_{K_{N,j},j};$$

in particular, $K_{1,j} = j$, since song j is most similar to itself;

2. For each column (song) compute the *rank of song j* as $R_j = \min\{l > 1 \mid K_{l,j} \text{ is a cover song of } j\}$, i.e., R_j is the rank (position) of the most similar cover song of j ;
3. Compute $MR = \frac{1}{N} \sum_j R_j$.

This algorithm is illustrated in Figure 3.11.

Mean Reciprocal Rank (MRR)

The reciprocal rank is defined as the inverse of a rank [DBEJ08]. In the **CSI** problem we are accounting ranks to the first version song that appears on the list ordered by similarity values of retrieved songs. We compute the ranks of the first retrieved version for every song on the database, then we take the inverse of these ranks. Finally, we compute the mean of these reciprocal ranks, obtaining the **Mean Reciprocal Rank (MRR)**. This quality measure is computed from the similarity matrix $S \in \mathbb{R}^{N \times N}$ as follows:

1. Compute $R_j, j = 1, \dots, N$ as in Mean Rank;
2. Compute $MRR = \frac{1}{N} \sum_j \frac{1}{R_j}$.

Median Rank (MDR)

The **Median Rank (MDR)** is another metric based on statistics of the first retrieved songs' ranks. The ranks are computed equally to **MR** and **MRR**, and after that the median is computed.

Mean Average Precision (MAP)

Kim Falk [Fal19] defines **Mean Average Precision (MAP)** in the context of recommender systems, in which users perform queries, and each query returns a list of ranked items.

- Precision at K ($P@k$):
is the number of relevant items found on the first k items
- Average Precision (AP):
 $AP(u) = \frac{1}{m} \sum_{k=1}^m P@k(u)$
where m is the length of the ranked list, and u is the user performing the query
- Mean Average Precision (MAP):
 $MAP = \frac{1}{|U|} \sum_{u \in U} AP(u)$
where U is the set of all users performing queries

Top at N

The group of metrics called Top at N (**Top@N**) is simply the number of relevant items that are present in the top N items. The parameter N usually is set to 1, 10, 100, and 1000.

3.2 Cover song classification

There is a related problem to the **CSI** one that it is called **Cover Song Classification (CSC)**. Instead of receiving one query song as input, a **CSC** system receives a pair of songs. The goal of this system is to classify this pair as versions of each other or not. We clearly have here a binary classification problem. From this point on, we will refer to an original/cover pair as “a pair labeled as 1”, and an original/non-cover pair as “a pair labeled as 0”. We also will refer to an input pair of songs as “reference/test” or “query/target” when it is not clear if it is a pair labeled as 1 or 0.

Ravuri and Ellis [RE10] are the first authors to implement a system that handles the **CSC** problem. The system receives a pair of songs as input, then computes beat-synchronous chromagrams for both. The beat tracker is executed 3 times, each time trying to favor the detected song's basic beat to be as close as possible to 240 BPM, 120 BPM, and 60 BPM, respectively. The authors propose 3 ways to compare the features from the pair of songs, which leads to 9 score values per pair, since each pair are represented by 3 distinct beat-synchronous chromagrams.

The first method to compare chromagrams starts with a square-root compression (as a post-processing step to the feature extraction process). Then a cross-correlation of the reference chromagram and the test chromagram is performed in order to highlight fragments that match. In this process all 12 circular shifts of the test chromagram are considered. Next, high-pass filtering is performed to emphasize sharp local maxima, where the authors consider to be the genuine matches. Lastly, the score is calculated as the value of the maximum peak. The second method to compare chromagrams has its score equally defined, only with an extra normalization of each chroma before computing the cross-correlation, so that the energy in each beat has unit sum.

The third method is built on top of a binary similarity matrix, computed from all chromagram pairs using the method defined by Serrà and Gómez [SG07]. Then the Smith Waterman algorithm is used to find the best local alignment in this matrix, using the technique published by Serrà et al. [SGHS08]. Finally, the score is the highest value related to the maximum similarity between the two chromagrams.

After computing the 9 scores (3 scores for each of the 3 types of features), the values are post-processed and placed in a vector. This 9D vector is used as the sample to represent the pair of reference/test songs in the classification step. For that they used two different classifiers - **Support Vector Machine (SVM)** and **Multi-Layer Perceptron (MLP)** - which are trained with manually annotated samples, and at last they are able to classify pairs of songs as being 1's or 0's. Figure 3.12 shows the block diagram of the system.

Figure 3.12: The diagram of the Cover Song Classification system developed by Ravuri and Ellis [RE10].

Salamon et al. [SSG12] when approaching the CSC problem consider three different representations: harmony, melody and bass line. The harmonic feature is a 12-bin HPCP computed in the range of 50Hz to 5000Hz, and through the use of normalization, tuning estimation and spectral whitening.

The melody representation is obtained using a melody extraction algorithm developed by Salamon and Gómez [SG12b]. This same algorithm is adapted to extract the bass line. A low-pass filter is applied at 261.6Hz, the window size is increased to 185ms (for better frequency resolution at low frequencies), only 2 octaves are considered (within the range of 27.5Hz to 110Hz), among other details [SSG12].

After that, the melody and bass line sequences are post-processed in order to handle variations between versions. All frequency values are converted to cents, and two types of abstraction are applied: semitone abstraction (to filter local variations) and octave abstraction (to remove octave displacements).

The similarity between two songs is computed using the Q_{max} algorithm, which is proposed by Serrà et al. [SSA09] as a dynamic programming method for computing the best local alignment from two time series. The distances from the 3 representations (HPCP, melody, bass line) are gathered to be the sample to represent the pair of songs.

The classification process is as follows: 5 disjoint balanced sets of query/target pairs of songs are selected; the corresponding samples are used to train 5 different classifiers (random forest, SVM, logistic regression, k-star, and Bayesian network); the classifiers are used to determine if two songs are versions or not.

Figure 3.13: The complete diagram of the processing steps presented by Salamon et al. [SSG12].

3.2.1 Cover song classification quality measures

Accuracy

Our first quality measure for the CSC problem is the accuracy. Let y_{test} be the annotations of the tested samples, and $y_{predicted}$ be the predicted classes from a classifier, the accuracy value is:

$$\text{accuracy}(y_{test}, y_{predicted}) = \frac{1}{N} \sum_{i=1}^N \text{equals}(y_{i_{test}}, y_{i_{predicted}})$$

$$\text{where } \text{equals}(a, b) = \begin{cases} 1, & \text{if } a = b \\ 0, & \text{if } a \neq b \end{cases}$$

Precision, recall and f1-score

In a binary classification problem such as the CSC we can use other quality measures such as precision, recall and f1-score. The table below shows how samples can be called according to how they are classified.

		Annotated label	
		1	0
Predicted label	1	true positive	false positive
	0	false negative	true negative

Using this taxonomy we can define the three quality measures with the following formulas:

$$\text{precision} = \frac{\text{true positive}}{\text{true positive} + \text{false positive}}$$

$$\text{recall} = \frac{\text{true positive}}{\text{true positive} + \text{false negative}}$$

$$\text{f1-score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

Precision is the number of correct classifications of covers over the number of all (correct or wrong) classifications of covers, recall is the number of correct classifications of covers over the number of samples labeled as covers (independent if they are classified correctly), and f1-score is the harmonic mean of precision and recall.

Chapter 4

Dataset Modifications

In order either to achieve better performance or to achieve better results several works on the literature perform modifications on selected datasets by replacing the full-length recordings to alternative versions of them.

It is important to clarify that the dataset modifications considered here are fundamentally different from dataset augmentation. Dataset modifications aim at replacing the entire dataset with new data based on a single type of transformation applied to the original data. In contrast, dataset augmentation aims at enlarging the dataset, by creating new modified data using several types of transformation.

For instance, consider a basic binary classification problem aiming at identifying cats and dogs. One plausible dataset modification might introduce noise to all images, replacing the original noise-free data, in order to improve the tolerance of the classifier to noise. A typical data augmentation process would perform several transformations to the image files (rotation, scaling, cropping, etc), adding the transformed files to the same dataset, alongside the original images. The main goal would be to obtain a considerably larger training set, which would indirectly improve the robustness of the classifier.

The main difference therefore between the two techniques is related to their goals: dataset modifications focus on specific transformations of the data, whereas dataset augmentation focuses on producing more training data.

This research explores dataset modifications in the context of music similarity, based on transformations that are presented below.

4.1 Segment selection

Levy and Sandler [LS06] present a system to search for songs that uses a content-based music similarity technique. This technique relies on segment models in order to achieve better time and memory performances. The algorithm that performs the segmentation of the songs, and selects thumbnails to replace the full-length songs, works as follows:

- extract beat-synchronous constant-Q spectrogram
- train a HMM on these features where each hidden state represents a distinct type of timbre found over the song
- use Viterbi algorithm to decode features into sequence of types of timbre
- label each beat with its type of timbre
- compute normalized histograms of these types of timbre for every 7-beat window
- cluster the histogram in order to define the segment boundaries (details about this clustering step are presented by Levy et al. [LSC06])

The algorithm that receives the segmentation as input and decides which thumbnail should be selected works as follows:

- count the segments
- find the most frequent types of timbre
- (if necessary) untie the first place by choosing the type of timbre whose segments have the highest mean energy (under the hypothesis that some sections such as choruses – the desired ones – are stronger than other ones such as verses)
- select the second segment of the most frequent type of timbre (under the assumption that sections towards the middle of a song are more representative of it, comparing with sections at the boundaries)

In a search task, the thumbnail for the query song is computed, and then the first 20 [Mel-Frequency Cepstral Coefficients \(MFCC\)](#) are extracted from it. Then a single Gaussian is fitted to these features, and a vector composed of the means and covariances concatenated is selected as global feature. Finally, two parameter vectors are compared using a symmetric version of the Kullback-Leibler divergence. The most similar (less distant) songs from the collection are presented to the user in an ordered list.

Bozzon et al. [[BPVT08](#)] develop a method for content-based music recommendation that relies on the similarity of semantic segments. They argue that the exploitation of semantic segmentation can lead to more meaningful results to the users. The semantic segmentation algorithm is proposed by Ong and Herrera [[OH05](#)] and can be divided in two main phases:

1. Phase 1: “detecting boundaries”

- segment the audio file using window length of 4096 samples, and hop size of 512 samples
- compute [MFCC](#) and sub-bands energy
- calculate all inter-frame cosine distances, and store the values in one similarity matrix for each feature
- enhance each similarity matrix using morphological filtering [[BFW04](#)]
- compute novelty measures correlating the matrices with a 2×2 kernel [[F000](#)]
- detect the 40 local maxima on the novelty curves, and use them as candidates for segment boundaries

2. Phase 2: “refining detected boundaries”

- perform a second segmentation of the audio file, but now using the detected boundaries
- compute 8 new features – [Zero Crossing Rate \(ZCR\)](#), spectral centroid, flatness, roll-off, flux, [Root Mean Square \(RMS\)](#), low bass energy, high-medium energy – for every segment
- calculate inter-segment Euclidean distances from the average values of these features
- repeat the same steps of phase 1 in order to compute new novelty curves
- divide the peaks in two groups: P and E , where P contains peaks above a predefined threshold, and E below this threshold
- order all peaks in P according to their indexes, order all peaks in E according to their values, and apply the following routine:
 - starting with the highest peak on E
 - if it is temporally distant 4 seconds (at most) from any peak on P , then insert it in P

- otherwise, delete it
- start over until there are no peaks left in E
- return P

After song semantic segmentation, the method extracts a 25-dimensional feature vector (1 ZCR + 1 spectral centroid + 1 spectral roll-off + 1 spectral flux + 1 spectral flatness + 20 MFCC) from each segment windowed every 100ms with 40ms overlapping. The feature vectors for all segments are summarized using a single Gaussian, and the global feature is the concatenation of the means and covariances. Finally, the inter-segment similarity is computed using Kullbak-Leibler divergence, and the inter-song similarity is computed according to the process described below.

For a query song q and the collection of songs B , they define the sets of segments S_q and $S_b, \forall b \in B$. Both sets are filtered (segments shorter than 10s are deleted) and then a graph is constructed with nodes that represent all elements from the sets, and edges that connect all nodes from S_q to all nodes from $S_b, \forall b \in B$. The edges are weighted by the distances between the segments. Finally, a graph reduction algorithm is applied, discarding edges with low similarity values, but maintaining full connectivity between the segments from both songs. The remaining edges are used to compute the overall similarity between the two songs as shown in this formula:

$$\text{similarity}(q, b) = \frac{1}{|A(q, b)|} \sum_{u=1}^{|A(q, b)|} w_u$$

where $A(q, b)$ is the set of edges that guarantees full coverage on the sets S_q and S_b , and w_u is the weight associated with the edge $e_u \in A(q, b)$.

Balen et al. [VBBWV14] perform a few experiments on Cover Song Identification (CSI) using cognitive audio descriptors. In the first experiment they use full-length songs from the chosen dataset; in the second experiment they use segment candidates returned by the algorithm proposed by Serrá et al. [SMGA12] that works as follows:

- start with a time series $X = [x_1, \dots, x_{N'}]$ with length N' , where x_i can be a column vector

Figure 4.1: An example time series (reproduced from [SMGA12])

The time series presented in Figure 4.1 is just for illustration, since the actual time series used as input for the segmentation task is Harmonic Pitch Class Profile (HPCP) [Góm06].

- compute $\hat{X} = [\hat{x}_1, \dots, \hat{x}_N]$ with length N , where $\hat{x}_i = [x_i^T x_{i-\tau}^T \dots x_{i-(m-1)\tau}^T]$, for $i = w+1, \dots, N'$, $w = (m-1)\tau$, m is the parameter that determines how much of the past is considered (chosen value by the authors is between 0 and 5 secs), τ is the parameter called time delay (chosen value is 1).

Figure 4.2: Time series computed considering past samples (reproduced from [SMGA12])

This step tries to mimic the human short-term memory by aggregating in the sample $\hat{x}_i$ information contained in the recent past. Figure 4.2 illustrates the new time series computed.

- calculate a square matrix R , where $R_{i,j} = \Theta(\epsilon_{i,j} - \|\hat{x}_i - \hat{x}_j\|)$, $\Theta(z) = \begin{cases} 1, & \text{if } z > 0 \\ 0, & \text{otherwise} \end{cases}$

$\|\cdot\|$ is the Euclidean norm, and $\epsilon_{i,j}$ represents a different threshold for each position (i, j) of the matrix R (details on how to compute $\epsilon_{i,j}$ can be found in the original paper [VBBW14]).

Figure 4.3: Matrix that stores the comparisons between all samples (reproduced from [SMGA12])

This third step is performed to look for repeated patterns, comparing all possible pairs of samples, and an example can be visualized on Figure 4.3.

- create a time-lag matrix L , where $L_{i,j} = R_{i,k+1}$ for i, j in $1, \dots, N$, $k = (i + j - 2)\%N$.

Figure 4.4: The time-lag matrix L (reproduced from [SMGA12])

This step (along with the next one) computes the so-called “structure features”, starting with the application of temporal lags, as illustrated in Figure 4.4.

- compute $P = L * G$, where $G = g_t g_l^T$, g_t and g_l being two Gaussian windows (with variances chosen to be $\sigma^2 = 0.16$) of sizes s_t and s_l (s_t set to around 30 sec; s_l set to 0.3 sec).

Figure 4.5: The estimated density P (reproduced from [SMGA12])

This is the second step of computing the “structure features”, and it consists in estimating a “bivariate probability density with Gaussian kernels” (the result can be seen in Figure 4.5).

- calculate $c = [c_1, \dots, c_{N-1}]$, a uni-dimensional novelty curve, where each $c_i = \|p_{i+1} - p_i\|^2$, $\|\cdot\|$ is the Euclidean norm, and c is linearly normalized between 0 and 1.

Figure 4.6: The novelty curve c (reproduced from [SMGA12])

This last step computes a novelty curve, and the peaks are considered as candidates for segment boundaries (as shown in Figure 4.6).

Finally, every c_i is considered as a peak if it is higher than a predefined threshold δ (set to 0.05), and also if it is a global maximum of a window centered in c_i and with length λ (set to 12 sec). The last step before declaring the segment boundaries is to add up $\frac{w}{2}$ to the peak indexes, to make up for the displacement included in the delay coordinates.

Returning to the experiments of Balen et al. [VBBWV14], they extract three features – Pitch Bi-histogram, Chroma Correlation Coefficients, and Harmonisation Feature – from all full-length songs in the first experiment. Then the features are whitened, transposed, weighted, and concatenated. The final representations are called *global fingerprints* which are compared to each other using cosine distance. When the program receives a query song, 12 global fingerprints are computed from it (regarding every transposition), and then compared with all stored fingerprints pre-computed from the entire collection. Then, a ranked list is returned for evaluation.

The second experiment uses the segmentation method presented above, and two non-overlapping thumbnails are selected from the returned segments list as follows:

- perform a simplification on the sequence of segment labels by merging repeated patterns:

$$ababXabXX \implies YYXYXX$$

- compute the duration of segments for all labels

- find the 2 labels whose segments cover the music most
- return the boundaries of the first instances of the 2 selected labels

Finally the method computes 24 new fingerprints, in the same manner as in the previous experiment, regarding 12 transpositions of each thumbnail.

Silva et al. [SdSB15] propose a technique for CSI which is based on the similarity of music shapelets. The concept of shapelets comes from time series classification, and the authors of this paper are inspired in the work done by Ye and Keogh [YK09]. In the context of time series classification, a shapelet is a subsequence of one time series which is most representative of its class. For every class on the classification problem they select a shapelet from one of its samples to be used to train a decision tree. The steps of the training phase can be summarized as follows:

- select candidates for shapelets computing all subsequences whose lengths are between min_{len} and max_{len} (user-defined parameters) from all training time series of the dataset D
- compute the distance values of each candidate to all original time series (since the length l of a subsequence s is smaller than the length of a time series T , the minimum of the Euclidean distances of s and every subsequence s' of T whose length is also l is computed)
- (for every candidate) order the distances and finds the optimal splitting point
 - find a distance threshold that, from it, D is split into two subsets D_1 and D_2 , such that $\forall T_1 \in D_1, dist(T_1, S) < d_{th}$ and $\forall T_2 \in D_2, dist(T_2, S) \geq d_{th}$ (S is the shapelet candidate)
 - this distance threshold d_{th} is considered optimal when $Gain(S, d_{th}) \geq Gain(S, d'_{th})$ for any other possible distance threshold d'_{th} ,
 - $Gain$ is defined as $Gain(splitting_point) = I(D) - \hat{I}(D)$
 - $I(D)$ is the entropy of D before the split; $\hat{I}(D)$ is the entropy of D after the split
 - $I(D) = -p(A)\log(p(A)) - p(B)\log(p(B))$, where p defines the proportion of elements in each class
 - $\hat{I}(D) = f(D_1)I(D_1) + f(D_2)I(D_2)$, where f defines the fraction of elements in each subset
- finally, after computing all optimal split points for all shapelet candidates (and their respective gain of information values), the chosen shapelet is the one that has the highest gain.

This method of shapelets is adapted by Silva et al. [SdSB15] in 5 aspects in order to be used in the CSI problem.

1. instead of using candidates with several different sizes (which can be very cumbersome) the authors reduce the set of possible subsequence lengths, and also use a hop size higher than 1
2. they replace the Euclidean distance by the [Dynamic Time Warping \(DTW\)](#) to compare the distance between subsequences and time series, since DTW is invariant with respect to time warpings
3. rather than performing a classification task based on information gain, they propose an alternative to assess a shapelet candidate's quality, according to this formula:

$$DistDiff(s) = \min_{i=1, \dots, n} (dist(s, OtherClass(i))) - \frac{1}{m} \sum_{i=1}^m dist(s, SameClass(i))$$

4. they select one shapelet for each song from the training set (as opposed to one shapelet per class)
5. the authors use three shapelets for each song (since the use of only one can be not very descriptive) which are selected by dividing the feature vector in three parts and using the method by Ye and Keogh [YK09] to select one shapelet for each third of the song

Finally, the process of querying is made by computing the distances from the input song to the triplets of every training song, averaging these three distances, and returning a ranked list.

4.2 Frame selection

The full-length songs can also be modified by selecting subsequences of them but now with non-contiguous segments, i.e., with a subset of frames that do not compose a contiguous segment. Seyerlehner [Sey10a] presents a tool to analyze which frames contributed the most to a similarity-based task when comparing two songs.

This tool shows that frames with low energy interfere substantially to the similarity value, because low energy frames have small Euclidean distance between them. Therefore, songs with several low frames are considered very similar by the computer, which contradicts what the author expects to be useful to a human listener (two songs are not going to be reported as similar simply because they share silent parts).

In order to obtain better similarity values, he proposes a method that perform the following steps:

- compute the spectrum for each frame
- map them to mel-scale
- sum the energy across all mel-bands for every frame
- sort the frames by their duration
- drop a percentile (for instance, 50%) of the low energy frames
- compute the similarity values using this new representations

Seyerlehner [Sey10a] also evaluates this frame selection method using two datasets, and removing low-energy frames corresponding to percentiles of 10%, 20%, ..., 90%. Besides comparing to the original dataset (0%) he also creates secondary datasets by removing random frames (also with percentiles from 10% to 90%) to verify if the selection of frames by energy actually makes sense.

Figure 4.7: Results obtained by the use of frame selection (reproduced from [Sey10a])

Figures 4.7a and 4.7b show the obtained results. We can observe that the datasets present best results with 70% and 80% respectively, comparing to the original dataset (0%) and to randomly removing frames (an artist filter is also applied, and details about it can be seen in the original paper [Sey10a]).

4.3 Source separation

As we mentioned before, the CSI literature states that the least common variable musical aspects between versions are the tonal ones [SGH10, SSG12, CLX17]. In Section 3.2 we cite a work done by Salamon et al. [SSG12] where they explore the isolated similarities from melody, bass line, and harmony representations. Foucard et al. [FDLR10] takes this approach to a next step, and uses a source separation algorithm (by Durrieu et al. [DRD09]) to isolate the main melody from the accompaniment.

The method by Foucard et al. [FDLR10] uses three representations for each song: the original mixture, the main melody, and the accompaniment. From each representation they extract a 36-bin HPCP averaged over all frames to compose the global features. When comparing two songs A and B they compute a matrix S according to the following formula:

$$S_{n,m} = \begin{cases} +1, & \text{if } OTI(h_{A,n}, h_{B,m}^{Tr}) \in \{0, 1, 35\} \\ -0.9, & \text{otherwise} \end{cases}$$

where $OTI(h_A, h_B) = \arg\max_{0 \leq i \leq 35} \{h_A \cdot \text{circular_shift}(h_B, i)\}$, $h_{A,n}$ is the n -th frame of song A , and $h_{B,m}^{Tr}$ is the (already transposed) m -th frame of song B .

From this matrix S they compute an alignment matrix H using an algorithm called **Dynamic Programming Local Alignment (DPLA)** (which is similar to DTW). This process is done for the three representations, so they obtain three matrices – H_{mix} , H_{mel} , and H_{acc} – which are combined to produce the final similarity value.

They select the maximum of each matrix as candidate for the overall similarity value, and consider the following sets: $\{M_{mix}, M_{mel}\}$, $\{M_{mix}, M_{acc}\}$, $\{M_{mel}, M_{acc}\}$, and $\{M_{mix}, M_{mel}, M_{acc}\}$, where M_{mix} is the maximum of H_{mix} , M_{mel} is the maximum of H_{mel} , and M_{acc} is the maximum of H_{acc} . For each set – which represents a different fusion scheme – they select the maximum again as final similarity value to be reported.

They also propose an early fusion process performed before calling **DPLA**. Using the three matrices S_{mix} , S_{mel} , and S_{acc} they produce a new matrix S , before calling **DPLA**, as follows:

$$S_{n,m} = \max(S_{n,m}^{mix}, S_{n,m}^{mel}, S_{n,m}^{acc})$$

All these alternatives are computed and illustrated in Figure 4.8. Table 4.1 shows the results they obtain, from which we consider the use of source separation encouraging as a pre-processing step for similarity-based tasks.

Figure 4.8: System's pipeline proposed by Foucard et al. [FDLR10].

	Precision	Mean rank ₁	Median rank ₁
Mix.	0.35	32.02	7
Acc.	0.34	33.18	7
Mel.	0.21	43.98	21
Mix., Acc.	0.37	31.41	5
Acc., Mel.	0.34	32.28	6.5
Mix., Mel.	0.35	31.18	7
Mix., Acc., Mel.	0.37	31.24	5
Early fusion	0.34	30.49	5.5

Table 4.1: Results obtained by the use of source separation (reproduced from [FDLR10])

Chapter 5

Methodology

In this chapter we concentrate all the original contributions of this research, which include implementations and experiments related to music similarity, cover song identification and classification, and dataset modifications.

5.1 A Framework for Music Similarity and Cover Song Identification

The first step in our exploration of music similarity corresponded to reviewing and exploring, through implementations and small experiments, extractors, aggregators, and distance functions appearing in the literature. These are summarized in Tables 5.1, 5.2 and 5.3 below, and form the building blocks for a proposed music similarity framework.

Chromagrams	Jensen et al. [JCEJ08]; Serrá et al. [SGHS08]; Yu et al. [YZL ⁺ 10]; Ravuri and Ellis [RE10];
MFCC	Foote [Foo97]; Logan and Salomon [LS01]; Aucouturier and Pachet [AP ⁺ 02]; Berenzweig et al. [BLEW04]; Pachet and Aucouturier [PA04]; Schnitzer et al. [SFW12];
Spectral features (centroid, bandwidth, etc)	Li and Ogiwara [LO04];
Tonnetz	Tymoczko [Tym09];
RMS	Panagiotakis and Tziritas [PT05]; McKay and Fujinaga [MF05];
ZCR	Gouyon et al. [GPD ⁺ 00]; Li and Ogiwara [LO04];
symbolic melodic sequences	Ghies et al. [GLCS95]; Tsai et al. [TYW ⁺ 05]; Frieler and Müllensiefen [FM05]; Marolt [Mar06]; Rho and Hwang [RH06a]; Salamon et al. [SSG13a];
Rhythm Pattern	Pampalk et al. [PRM02a]; Pampalk et al. [PFW ⁺ 05]; Seyerlehner et al. [SSPK10];

Table 5.1: Reviewed and explored list of extractors.

single Gaussian	Schnitzer et al. [SFW12];
Gaussian Mixture Model	Aucouturier and Pachet [AP ⁺ 02]; Pachet and Aucouturier [PA04]; Berenzweig et al. [BLEW04];
Vector Quantization	Logan and Salomon [LS01];
Markov Chain	Hoos et al. [HRG01];
Octave Abstraction	Salamon et al. [SSG13a];
Interval Abstraction	Salamon et al. [SSG13a];
Pitch Contour (3-levels)	Ghias et al. [GLCS95];
Pitch Contour (5-levels)	Rho and Hwang [RH06a];

Table 5.2: *Reviewed and explored list of aggregators.*

Manhattan distance	Seyerlehner et al. [SSPK10]; Knees and Schedl [KS13];
Euclidean distance	Foote [Foo97]; Li and Ogihara [LO04]; Yu et al. [YZL ⁺ 10];
Cosine distance	Foote [Foo97]; Tralie [Tra17];
LCS-based distance	Uitdenboger and Zobel [UZ99]; Kelly [Kel12];
Levenshtein’s distance	Lemström and Ukkonen [LU00]; Kelly [Kel12];
Kullback-Leibler distance	Berenzweig et al. [BLEW04]; Schnitzer et al. [SFW12];
Earth Mover’s distance	Logan and Salomon [LS01]; Typke et al. [TWV05];
Monte Carlo distance	Aucouturier and Pachet [AP ⁺ 02]; Pachet and Aucouturier [PA04];

Table 5.3: *Reviewed and explored list of distances.*

Notice that the previous lists do not contemplate all the techniques presented in Chapter 2. We actually started with a huge list of techniques that was altered in many ways (both discarding and collecting techniques along the research process).

An important criterion for this revision consisted in removing the techniques that do not have open source implementations. The rationale for this is to avoid producing implementations that might differ from the original techniques due to ambiguous or insufficient details in their textual descriptions. The survey of open source libraries (more details on Section 6.1) also led us to include techniques not found in the music similarity literature. For instance, the library that computes Rhythm Patterns¹ also implements Rhythm Histograms, Statistical Spectrum Descriptors, and Modulation Variance Descriptors, which have also been considered in our work.

This same criterion was applied to aggregator and distance techniques, but in a softer way, since they are simpler to implement. For instance, it only took one implementation of one clustering algorithm - k-means - to keep the vector quantization technique in the list (we implemented the remaining processing steps after the clustering of local features).

Music similarity models

The detailed analysis of the techniques in the literature produces one major observation: several papers do not explicitly argue as for why a particular extractor (or aggregator, or distance) is selected to solve a particular problem. Even less frequent are arguments about why a specific set of techniques are used in combination (instead of many other plausible alternatives). This prompted us to try to explore (the hundreds of) combinations that are not considered in the literature, instead of trying to reproduce (very closely) only a few papers. It was thus natural to look at this problem as a benchmark, exhaustively experimenting with lots of combinations of extractors, aggregators, distances, here referred to as *music similarity models*.

All the combinations of features, aggregators, and distances considered result in a total of 690 music similarity models; the complete list is available at <https://rppbodo.github.io/phd/music-similarity-models.html>. The number of models is not a basic multiplication of $n_{features} \times n_{aggregators} \times n_{distances}$ due

¹https://github.com/tuwien-musicir/rp_extract

to compatibility issues: not all aggregators can be used with all features, and not all distances can be used to compare all global features. Below we summarize how the music similarity models are built.

Every feature that corresponds to a numerical value (1-D feature), or a numerical vector (2-D feature), associated with each audio frame allows the use of statistical aggregation methods. Thus the melspectrogram, all the chromagrams ([Short-Time Fourier Transform \(STFT\)](#), [Constant-Q Transform \(CQT\)](#), [Chroma Energy Normalized Statistics \(CENS\)](#)), tonnetz, MFCC, all spectral features (centroid, bandwidth, roll-off, flatness, contrast), RMS, and ZCR can be aggregated through single or multivariate Gaussians (please refer to Section 2.2 to check all the Gaussian variations considered). Alternatively, Gaussian Mixture Model and Vector Quantization can also be used as aggregation methods for these features.

The symbolic domain feature called Pitch Contour Segmentation is aggregated with 5 methods: octave abstraction, interval abstraction, pitch contour with 3 levels, pitch contour with 5 levels, and Markov chain.

The remaining features – Rhythm Pattern, Rhythm Histogram, Temporal Rhythm Histogram, Statistical Spectrum Descriptor, Temporal Statistical Spectrum Descriptor, and Modulation Variance Descriptor – are already aggregations of local features by definition, and thus we do not aggregate them further (this is identified by the aggregation method *bypass*).

Every global feature that corresponds to a numerical vector (for instance, concatenated parameters from statistical models) can be seen as a point in the vector space $\mathbb{R}^n$, and can be compared to one another using spatial distances such as Euclidean, Manhattan, Chebyshev, and cosine. The aggregators that are compatible with these 4 distances are basic statistics, difference statistics, statistical summarization, [Gaussian Mixture Model \(GMM\)](#), vector quantization, and Markov chain.

Statistical models can also be viewed as computational models, allowing us to draw random samples from them and access their probability density functions. Thereby we can compare them using Kullback Leibler, Earth Mover’s and Monte Carlo distances. Finally, all symbolic global features can be compared with [Longest Common Subsequence \(LCS\)](#)-based and Levenshtein distances.

Implementation details

In our work, all these models and methods were incorporated into a music similarity framework, implemented according to the architecture illustrated in Figure 5.1.

Figure 5.1: Processing diagram for the implementation of our music similarity framework.

The data cleaner module processes an input dataset and performs data cleaning tasks, as presented in Section 6.3; the feature extractor module extracts the named feature for all audio files of the dataset; the pre-aggregation module computes information that is required by some aggregation functions (for instance, if the selected aggregation method is vector quantization, this module computes the codebook); the feature aggregator module computes global features from local ones; the pre-distance module computes information required by some distance functions (for instance, computes the [Optimal Transposition Index \(OTI\)](#) from every pair of songs before measuring the distance between them); the distance calculator module computes the distances between global features for all possible track pairs, and returns the similarity matrix (as described in Section 2.4) and a set of chosen metrics. If the “pure” music similarity problem is selected, it returns intra-inter-class similarity ratios; if the [Cover Song Identification \(CSI\)](#) problem is selected, it returns [Mean Rank \(MR\)](#), [Mean Reciprocal Rank \(MRR\)](#), [Median Rank \(MDR\)](#), [Mean Average Precision \(MAP\)](#), etc. The source code of our music similarity framework is available at <https://github.com/rppbodo/music-similarity-framework>.

Every module may be executed as a single thread or in multi-thread mode. They also save all computed data to disk for future executions, which can lead to a considerable time gain. For illustration, it takes 14m54.096s to extract melspectrograms for a dataset of 160 tracks with a single thread of a *Intel(R) Core(TM) i5-5200U CPU @ 2.20GHz* processor, while it only takes 0m7.861s to load the same pre-computed data from the hard disk.

Relevant metrics for task-specific music similarity models

Even though the inter-intra-class similarity ratio is an useful metric to assess a music similarity model’s overall quality, specific tasks often require specific metrics that best capture the specificities of the application domain. For instance, we use two datasets that were designed for the query by singing/humming task, and MIREX 2020² defined *top-10 hit rate* as the evaluation metric for the Query by Singing/Humming competition. As already pointed out in Chapter 1, the very notion of

²https://www.music-ir.org/mirex/wiki/2020:Query_by_Singing/Humming

music similarity always exist within some specified context, which influences how music similarity expresses itself and how music similarity models should be evaluated.

In order to evaluate the use of our music similarity framework within the context of one specific application of music similarity, and its related datasets, we consider the Cover Song Identification problem, introduced in Section 3.1. This is a well-suited problem for the evaluation of the framework for two main reasons: on the one hand, a cover song always has musical elements which are similar to those of the original song; on the other hand, the specific musical elements (melody, rhythm, etc), as well as the specific way in which they are similar (between cover song and original) can be very subtle and diverse, suggesting that different models may be better suited to identify cover songs written in different styles or using different music strategies.

5.2 Cover Song Classification

Besides considering CSI, we also investigate the Cover Song Classification (CSC) problem, in order to address the differences between the search for covers within a dataset and the binary classification of a pair of songs (whether they are versions of each other or not). Inspired by fusion CSI methods (see Section 3.1.3) we investigated the use of combined information from several music similarity models, in order to attempt to produce better similarity models in a constructive (or collaborative) way. The act of gathering information from different models can be categorized as an early fusion scheme, since we are blending data before the classification step, according to Ning Chen et al. [CLX17]. Figure 5.2 presents the proposed processing pipeline for the CSC problem.

Figure 5.2: The proposed processing pipeline for the Cover Song Classification problem.

The first element in the pipeline of Figure 5.2 is the music similarity framework presented above. A group of m similarity models is selected, and the corresponding similarity matrices are gathered to be fused, incorporating information from distinct models. In order not to interrupt the presentation of the pipeline, we postpone the discussion of model selection strategies to the end of this section. The m similarity matrices returned by the music similarity framework are stacked to form a tensor with dimension (m, n, n) , where n is the number of tracks in the processed dataset.

In the sample creator module the tensor is traversed (as seen in Figure 5.3) to produce the samples for classification, which in this case correspond to pairs of songs. The sample that represents

the $(\text{song}_i, \text{song}_j)$ pair is the vector obtained by traversing the tensor through the positions $(*, i, j)$. Semantically, the samples may be viewed as sets of different opinions on how similar song_i and song_j are from different perspectives (i.e., lists of scores from distinct music similarity models).

Figure 5.3: An example of a tensor built from several similarity matrices, and the sample vector $(*, i, j)$.

Experiments with classification require disjoint training and testing sets. This makes sense since it is not fair to test the classifier with a sample that has been already seen in the training phase. In the **CSC** problem, a sample holds information about 2 songs, so if we select a sample $(*, i, j)$ to be in the training set, every sample $(*, k, l)$ in the test set must satisfy $k \neq i, j$ and $l \neq i, j$. This shows that in order to create such a train test split it is necessary to place original songs along with their versions together in the same split.

Considering that a train test split has to partition the samples, which represent song pairs, according to a given ratio, and at the same time satisfy the above constraint, some care must be taken as we assign groups of songs (originals along with their versions) to the train or test set. It should be clear that in order to produce for instance a 70%-30% train test split, i.e., having 70% of the *pairs* in the training set and 30% of the pairs in the test set, one cannot simply assign 70% and 30% of the original songs respectively to the train and test sets, because the number of versions for each original song may be wildly different.

We propose the following heuristic approach to solve this problem. We start with empty train and test sets, and sort the original songs by their corresponding number of versions, in descending order. Beginning with the first original song (i.e. the one that has the largest number of versions and thus can have the largest impact in the split percentages), we assign it to the split that is farthest from its target percentage (this would typically be the train split). We then proceed to the next original song, and compute the difference between the current split percentages and the desired split. If the train set corresponds to the largest difference, the current original song (along with its versions) is added to the train set. Analogously, the current song with its versions are added to the test set if this split is farthest from its target percentage. This heuristic is formalized in the following pseudo-code.

```

1: function SPLIT_TRAIN_TEST_HEURISTIC(original_songs, train_percentage)
2:     ▷ original_songs is sorted by the number of versions in descending order
3:     test_percentage = 1 - train_percentage
4:     train_set ← []
5:     test_set ← []
6:     for all song ∈ original_songs do
7:         total ← length(train_set)**2 + length(test_set)**2
8:         if total == 0 then
9:             train_set.append(retrieve_all_covers(song))
10:        else
11:            current_train_percentage ← length(train_set)**2 / total
12:            current_test_percentage ← length(test_set)**2 / total
13:            train_distance ← train_percentage - current_train_percentage
14:            test_distance ← test_percentage - current_test_percentage
15:            if train_distance ≥ test_distance then
16:                train_set.append(retrieve_all_covers(song))
17:            else
18:                test_set.append(retrieve_all_covers(song))
19:            end if
20:        end if
21:    end for
22:    return train_set, test_set
23: end function

```

Regarding the actual classification step, just as in any machine learning problem, we start with the learning step, where the classification model is fitted to the training samples. After that, we ask the classifier to predict the classes for all testing samples. In the implemented pipeline we worked with the following classification models:

- naive Bayes
- logistic regression
- decision tree
- random forest
- ada boost

The last module, called Metrics Calculator, receives the predicted and ground-truth labels, and computes all the metrics discussed in Section 3.1.4.

We now discuss how to select the music similarity models to create the tensors from which we extract the samples for the classification task. We start by ordering the models according to their quality in the CSI problem using MR values, which proved to be a quite reliable measure of the models' quality.

A somewhat natural idea is to select the Top-N models, since they are supposed to provide the most reliable similarity measures for the classification task. However, the best models are usually very similar to each other: they are usually tonal features, with statistical aggregation methods, and vector space distances. Thus, we aimed to explore alternative model selection strategies that would avoid to include very similar techniques (e.g., `chroma_stft` and `beat_synchronous_chroma_stft`) that appear close in the Top-N list, and prefer more complementary ideas (e.g., a rhythmic descriptor) that might appear just a few positions ahead in the same list.

The solution we propose is to cluster similar techniques (feature, aggregator or distance) into equivalence classes, and, when traversing the sorted list of models, we only select models with at

least one technique that has not been selected before. The manually clustered techniques are shown in Figures 5.4, 5.5, and 5.6.

Figure 5.4: *The manually clustered extractors.*

Figure 5.5: *The manually clustered aggregators.*

Figure 5.6: *The manually clustered distances.*

5.3 Cover Song Identification and Classification

For every classifier in the previous section it is possible to obtain a likelihood estimation for samples (pairs of songs), prior to the binary classification. For our specific problem, this means that for every trained classifier we may obtain a chance for a pair of songs to be versions of the same work, according to the trained model. This secondary information obtained from the **CSC** experiments can be used in the **CSI** context as scores, and by aggregating these scores for every pair of songs from a dataset, we may define a new similarity matrix. This similarity matrix can thus be used to solve the **CSI** problem, and be evaluated within that context using the relevant metrics (**MR**, **MRR**, **MDR**, **MAP**, etc).

There is one issue with this idea: in the **CSC** problem, described in the preceding section, samples are divided into two disjoint sets (training and test). According to good machine learning practices, the classifier should only be used to obtain these chance values of the test samples (because it knows the ground truth values for the training samples). Even if we did try to train two separate classifiers by swapping the train/test sets as illustrated in Figure 5.7, we would still be far from solving the issue: on the one hand, it would be unusual and ineffective to train a classifier on a set smaller than the test set; on the other hand, this would still leave out many samples (the white cells in Figure 5.7). This issue does not appear to have a simple solution if both training and test samples are obtained from the same dataset.

Figure 5.7: *A naive solution to obtain the most of chance values for the test samples of a single dataset.*

An alternative (and better) method is to perform a cross-dataset classification, using a larger dataset *A* to train the classifier, and a smaller dataset *B* to obtain the estimated chance values for all pairs of songs in *B*, as exhibited in Figure 5.8. This method allows us to produce a similarity matrix for dataset *B* that embodies the knowledge of the classifier trained on dataset *A*. Thus, a

solution to the CSC problem can be used in the CSI problem, as long as the classifier computes likelihood estimates prior to the binary classification.

Figure 5.8: A proper solution to obtain chance values for all samples of one dataset using a second larger dataset for training.

The complete process of using a CSC classifier for CSI is quite similar to the CSC pipeline, so we skip a step-by-step explanation, but refer to Figure 5.9, where two parallel pipelines represent the training phase (with dataset *A*) and predicting phase (with dataset *B*). We observe that, due to the different datasets involved, these parallel lines could be executed concurrently. The classifier is trained with k^2 samples from dataset *A*, and only after that, it receives the l^2 pairs of songs from dataset *B* to produce values between 0 and 1, interpreted as chances of the samples to be from pairs of versions.

Figure 5.9: The full processing pipeline connecting cover song identification and cover song classification.

Finally, a small adjustment is required in the choice of the music similarity models that are combined, because we have now two datasets (train and test). Each dataset produces a different list for the Top-*N* best similarity models, with potentially conflicting quality values for the similarity models that are common to both lists. Additionally, there is the issue of filtering out models which are considered equivalent (for combining similar feature/aggregation/distance techniques).

The solution we propose builds a centralized list of music similarity models ordered by their quality values (mean ranks), and works as follows. Consider that we have *N* datasets, along with

the mean rank values for all music similarity models considered (in our research, this corresponds to 690 models). Switching perspectives, we can see that for each similarity model we have N mean ranks (one for each dataset). We want to represent each model using a single value, so we can order the models (chain ordering is not useful here, because there is no a priori preference for any particular dataset).

Considering that the same similarity model may perform very differently on different datasets, we would like to get a sense of the central tendency of the values corresponding to each particular model, and also of their dispersion (which could be used to break ties). The most obvious statistics that come to mind are mean and standard deviation; however, these are quite sensitive to outliers. For this reason we propose using robust statistics for representing central tendency and statistical dispersion, namely median and median absolute deviation, respectively.

5.4 Dataset Modifications

As we have seen on Chapter 4, data modifications have been used in order to improve results for [Music Information Retrieval \(MIR\)](#) tasks, with a decrease in computational effort when the modified audio files tend to be considerably smaller than the original ones.

5.4.1 Segment selection

Segment selection is the first dataset modification considered here. It is motivated by the potential computational impact of substituting full-length songs for much smaller songs snippets, and also by the fact that online datasets are subject to copyright restrictions and usually cannot provide complete songs.

The basic idea of segment selection is to create a modified dataset where each song is replaced by a representative segment, such as a chorus or refrain. Several strategies for selecting representative song segments are detailed in the sequel.

Segment selection via music segmentation

Music segmentation algorithms are natural candidates for segment selection, since they look for repetitive patterns in a song by analyzing music structure. These algorithms produce segmentation profiles such as the one displayed in Table 5.4, with labels denoting repeating segments.

start time	end time	segment label
0.0	2.9000	G
2.9000	17.8200	F
17.8200	30.9880	D
30.9880	86.6440	A
86.6440	99.2800	F
99.2800	108.3440	A
108.3440	121.7800	D
121.7800	158.3240	A
158.3240	181.6040	F
181.6040	204.9400	A
204.9400	224.9280	F
224.9280	265.4800	E
265.4800	265.5200	G

Table 5.4: An example segmentation computed using the SI-PLCA algorithm.

Given a segmentation of a song, a representative segment could be chosen for instance as the most frequent segment with duration above 30 seconds. This allows us to generate a new modified

dataset, by substituting a song for its representative segment. Three different music segmentation algorithms are included in our evaluation and detailed below.

Levy and Sandler [LS08] propose an algorithm for audio segmentation that consists in extracting spectral features, post-processing them, and reducing their dimensionality using [Principal Component Analysis \(PCA\)](#). The resulting 20-dimensional vector with the principal components of each frame is then appended with the corresponding spectrum norm, resulting in the final feature vector. An [Hidden Markov Model \(HMM\)](#) is then trained with all the feature vectors, and Viterbi algorithm is used to decode each song into a sequence of labels, which represents a low-level labeling for every frame of the song. Histograms are produced to represent the distribution of these low-level labels and their neighboring labels. Frame sequences are finally grouped into labeled segments by clustering these histograms, using an algorithm that considers temporal continuity constraints via a Markov random field. Such labeled segments correspond to the structural segmentations for each track.

Mauch et al. [MND09] present a segmentation algorithm in the context of automatic chord transcription. It starts by extracting chroma vectors for every beat of each song. Then it builds a self-similarity matrix comparing all pairs of chromas using Pearson correlation coefficients. This matrix is smoothed via low-pass filtering, and diagonals are traversed to locate repetitions. Repeating segments are then clustered using heuristics to discard sub-segments and choose among overlapping segments, and favoring those segments with largest coverage of the song (coverage is measured by a segment's length multiplied by its number of repetitions).

Weiss and Bello [Bel10] propose a technique called [Shift-Invariant Probabilistic Latent Component Analysis \(SI-PLCA\)](#) which is used to decompose beat-synchronous chromagrams into repetitive patterns and their temporal occurrences, which encodes the temporal structure within the songs. SI-PLCA is built incrementally on top of the [Non-negative Matrix Factorization \(NMF\)](#) technique, which decomposes a non-negative matrix V , representing an audio signal, into two matrices – $V \approx WH$ – where the columns of W are templates occurring in V , and the rows of H are the activations of these templates in V . They first define the [Probabilistic Latent Component Analysis \(PLCA\)](#), which is a probabilistic variant of NMF, where both columns of W and rows of H are interpreted as multinomial probability distributions, and columns of W are interpreted as basis functions. A new distribution is added as weights for each basis function, resulting in a new factorization $V \approx WZH$, where Z is a diagonal matrix with the weight distributions. The technique SI-PLCA is derived from PLCA by adding the property of shift invariance. This is done by modifying the basis functions to include L templates instead of a single template as in PLCA. So the basis functions become matrices instead of vectors, and W becomes a tensor.

Segment selection via thumbnailing

Thumbnailing algorithms can also be used to produce candidate segments meant to replace full-length recordings in modified datasets. Two such algorithms are included in our evaluation.

Cooper and Foote [CF02] propose a method to select thumbnails from songs that uses parameterized versions of audio signals through MFCC analysis, producing compact representations for every frame. From the MFCC it builds a [Self-Similarity Matrix \(SSM\)](#) S using cosine distance between frames, and then for every segment starting at index i and ending at $i + L$ the method defines its average similarity with respect to the whole song as $\hat{S}(i, i + L) = \frac{1}{NL} \sum_{m=i}^{i+L} \sum_{n=1}^N S(m, n)$. The thumbnail is selected by looking for the segment with maximum similarity to the entire song, that is, by finding i and L that maximizes $\hat{S}(i, i + L)$, subject to constraints on starting time and duration.

Bartsch and Wakefield [BW05] also work with a self-similarity matrix, but this is computed using the correlation of 12-bin chroma vectors extracted from beat-synchronous frames. A step of correlation filtering produces a modified self-similarity matrix, from which the thumbnail is obtained by selecting the maximum value of the new matrix, also subject to constraints on starting time and duration.

Other strategies for segment selection

Besides segmentation and thumbnailing algorithms, we also considered the selection of the beginning, middle and end portions of the songs, as is frequently done in the context of music information retrieval [TC02a]. We used the initial, mid-point and final slices of 30s for each song as representative segments, thus generating three modified datasets.

5.4.2 Frame selection

As in Seyerlehner’s work [Sey10a], discussed in Section 4.2, we also included frame selection in our experimental evaluation.

RMS values are computed for each song using 1024-sample frames. These values are sorted, and then a corresponding percentile (we use 10%, 20%, ..., 90%) of the lowest valued frames is discarded, resulting in a shortened version of the song with the remaining highest valued frames (in their original order). This produces nine secondary datasets (one modified dataset for each percentile). Figure 5.10 shows a 30 second audio clip (from the song Creep by Radiohead) and the selected 50% highest RMS valued frames highlighted in red.

Figure 5.10: *Frame selection keeping 50% of the frames with the highest RMS values.*

In addition to the above mentioned method, we aim to verify whether frames containing vocals would be more relevant to similarity measures than instrumental frames. For this purpose, we propose a novel frame selection method, using the RMS values from the vocal track³ as the sorting criterion and then applying a given percentile (again 10%, 20%, ..., 90%), similarly to the above mentioned frame selection method. Figure 5.11 (top audio clip) shows the isolated vocals from the same song as in Figure 5.10, and the 50% selected frames with higher (vocal) RMS values. Then the selected frame indexes are applied to the original track (bottom audio clip). This method produces nine modified datasets, one for each percentile.

³Vocal tracks are obtained using the Open-Unmix [SULM19] source separation algorithm.

Figure 5.11: *Frame selection from the vocals-only (top) 50% highest RMS values, and applying them to the mix (bottom).*

5.4.3 Source separation

Foucard et al. [FDLR10] consider that songs consist in a leading voice mixed with an accompaniment, and use separated sources in the context of music similarity and cover song detection. They compare not only the original songs but also the extracted melodies and the accompaniments, and fuse the comparison results using different strategies.

Based on their work, we consider the use of separated sources to measure different aspects of music similarity. For instance, we can use the separated vocal tracks of two songs to produce a measure of melodic similarity between them, and the isolated drum tracks for rhythmic similarity. We expect that, with the combined use of similarities obtained from different musical perspectives, we should be able to improve CSI results.

For the task of separating audio sources within a song recording, we use the Open-Unmix model [SULM19], which is currently considered the state-of-the-art in audio source separation. This algorithm returns four audio sources for each input, labeled “vocals”, “bass”, “drums”, and “other” (a generic track containing the remaining sources, after the separation of the previous three). For each given dataset, we use these separate tracks to build four new datasets, one corresponding to each individual source.

5.5 Fusion

As seen on Section 3.1.3, fusion techniques have been successfully applied in the context of CSI research. In the previous two sections we discussed dataset modification methods and source separation, where the idea is to explore different music similarity models applied to isolated sources. We propose here the use of fusion techniques to similarity matrices obtained from datasets containing distinct individual sources.

We start by combining the four self-similarity matrices, corresponding to the four sources produced by Open-Unmix [SULM19], by using the mean, minimum and maximum of the corresponding similarity values for each pair of songs. Specifically, if B , D , V , O are similarity matrices respectively obtained from the separate “bass”, “drums”, “vocals” and “other” modified datasets, we define the three following matrices:

- $Mean_{i,j} = mean([V_{i,j}, B_{i,j}, D_{i,j}, O_{i,j}]);$
- $Min_{i,j} = min([V_{i,j}, B_{i,j}, D_{i,j}, O_{i,j}]);$
- $Max_{i,j} = max([V_{i,j}, B_{i,j}, D_{i,j}, O_{i,j}]).$

We also include the [Similarity Network Fusion \(SNF\)](#) technique presented in Section 3.1.3 as a fourth fusion method, which corresponds to a more sophisticated approach to fusion in comparison to the basic statistics above.

In order to decide which models are included in the source separation fusion process, we explore the use of filtered lists of similarity models, as discussed in the context of the [CSC](#) problem. Basically, the Top-N list of the best similarity models (ranked according to their mean rank in the [CSI](#) problem) is filtered, considering the equivalence classes of similar techniques (feature, aggregator or distance), as illustrated in Figures 5.4, 5.5, and 5.6. This produces $M < N$ similarity models, which in turn are applied to the separate “bass”, “drums”, “vocals” and “other” modified datasets, producing 4 sets of M similarity matrices, one for each source. Finally, each possible 4-tuple of similarity matrices (i.e., “bass”, “drums”, “vocals” and “other”) is fused, producing M^4 fused similarity matrices.

Because it considers all such combinations of models and sources, the above method provides yet another way of combining multiple musical perspectives, by fusing for instance a melodic similarity model applied to vocals and bass, a rhythmic similarity model to the drums and a timbre-related similarity model to other sources, among many other possibilities.

Chapter 6

Experiments and Results

6.1 Technical choices

The programming language chosen for the implementation is Python, a generic language, with a large and active community, widely used in areas such as data analysis, machine learning, artificial intelligence, etc. In addition, there are several modules for Python directly linked to the tasks involved in our project.

- LibROSA¹

LibROSA is a module for audio analysis implemented and maintained by LabROSA² from Columbia University. It has several feature extractors, including melspectrogram, chromagrams, tonnetz, etc.

- Essentia³

Essentia is a library implemented in C++ with an encapsulation for Python, developed by the MTG⁴ at Pompeu Fabra University. It focus on musical analysis, and has a huge range of extractors: PitchMelodia, PitchContourSegmentation, [Mel-Frequency Cepstral Coefficients \(MFCC\)](#), etc.

- RP_extract⁵

This is the Python library that implements the Rhythm Pattern feature extractor along with its sibling features: Rhythm Histogram, Statistical Spectrum Descriptors, Modulation Variance Descriptors, etc.

- NumPy⁶

NumPy is a scientific computing module that has an N-dimensional array object (`ndarray`) widely used in our project to store and manipulate data (local features, global features, similarity matrices, etc). Any operation performed on tensors (such as ordering, searching, extracting basic statistics, adding, multiplying, among others) thus becomes trivial to implement with NumPy. Under the hood, these operations are also heavily optimized for speed.

- SciPy⁷

SciPy is a scientific computing library that contains most of the distance functions and statistical models used in our project.

¹<http://librosa.github.io/>

²<https://labrosa.ee.columbia.edu/>

³<http://essentia.upf.edu/>

⁴<https://www.upf.edu/web/mtg>

⁵https://github.com/tuwien-musicir/rp_extract

⁶<http://www.numpy.org/>

⁷<https://www.scipy.org/>

- matplotlib⁸

Matplotlib is a visual library for plotting graphics, and is used to produce virtually all figures presented in this thesis. It was also used to produce several graphics during the course of implementation, which served as guides for the process.

- scikit-learn⁹

This is arguably the most widely used tool for data analysis and machine learning in Python. Built on top of NumPy, SciPy, and matplotlib, it is extremely easy to use, with fast initial learning curve. It implements all the classifiers used in our experiments.

- multiprocessing

This module was used to implement all parallel computations, which are essential to reduce the processing time of the experiments, due to the large amount of audio files used.

- gzip + joblib

Two other modules of great importance for reducing the processing times of the experiments are gzip and joblib, which are used for storing data on disk, such as features, aggregations, distances and similarity matrices, so as not to perform those costly operations multiple times.

6.2 Datasets

Ballroom

The Ballroom¹⁰ dataset is composed of excerpts from several dance styles typically used in ballroom dancing. The audio files are provided by Ballroom Dancers website¹¹, and several annotations can also be found online. We use this dataset mainly for rhythmic similarity. All excerpts are classified according to the names of the dance styles. More details about the Ballroom dataset can be seen in Table 6.1.

number of classes	10
number of files	698
files per class distribution	heterogeneous (see Figure 6.1)
file format	.wav
duration (mean)	31.28103
duration (std)	0.75731
duration (min)	29.35
duration (max)	34.06

Table 6.1: *Extra information about Ballroom dataset.*

⁸<https://matplotlib.org/>

⁹<https://scikit-learn.org/stable/>

¹⁰<http://mtg.upf.edu/ismir2004/contest/tempoContest/node5.html>

¹¹<https://www.ballroomdancers.com/>

Figure 6.1: Histogram of files per class from Ballroom dataset.

GTZAN

Tzanetakis and Cook [TC02b] created a dataset called GTZAN¹² for the task of music genre classification. The authors claim that an effort was made to ensure that the audio files were representative of the corresponding musical genres. Furthermore, the files were obtained from several different sources (records, radios, ambient recordings with microphones, etc.) in order to represent a variety of recording conditions.

GTZAN is annotated with the musical genres of each audio file, and we use it mainly for timbre similarity, based on papers that seek to establish a correlation between genre and timbre, on the assumption that different genres employ different instruments. It is important to note that this is a simplifying hypothesis for which countless counter-examples can be easily produced. Meta-data for this dataset can be found in Table 6.2.

number of classes	10
number of files	1000
files per class distribution	homogeneous (100 files per class)
file format	.au
duration (mean)	30.02187
duration (std)	0.08117
duration (min)	29.93
duration (max)	30.65

Table 6.2: Extra information about GTZAN dataset.

IOACAS-QBH

IOACAS¹³ is a dataset compiled by the Institute of Acoustics (IOA) of the Chinese Academy of Sciences (CAS) for the query by humming task. It is composed of 298 ground-truth melodies (MIDI files), and 759 query melodies (WAVE files of singers humming the melodies). The MIDI files are converted to WAVE files using the FluidSynth¹⁴ command line tool. This dataset is used for melodic similarity, and the classes correspond to the individual melodies (each class contains

¹²<http://marsyas.info/downloads/datasets.html>

¹³http://mirllab.org/dataSet/public/IOACAS_QBH.rar

¹⁴<https://www.fluidsynth.org/>

a synthesized ground-truth melody and all of corresponding queries). More information about this dataset can be seen in Table 6.3.

number of classes	298
number of files	1057
files per class distribution	heterogeneous (see Figure 6.2)
file format	.wav
duration (mean)	65.58255
duration (std)	94.87213
duration (min)	7.22
duration (max)	721.25

Table 6.3: *Extra information about IOACAS-QBH dataset.*

Figure 6.2: *Histogram of files per class from IOACAS-QBH dataset.*

Maria Panteli’s melody dataset

Panteli and Dixon [PD⁺16] perform an evaluation of audio features in the context of melodic and rhythmic similarities. They create two datasets (one for each task) composed of synthesized audio, with controlled transformations applied to timbre, recording quality, global tempo, key transposition, and local tempo. These transformations are meant to enforce invariance properties upon the features used.

The melody dataset¹⁵ is composed of 30 main melodies divided in six musical styles, as follows:

- monophonic melodies:
 - 5 Dutch Folk
 - 5 Classical
 - 5 Byzantine
 - 5 Pop
- polyphonic melodies:
 - 5 Classical

¹⁵https://archive.org/details/panteli_maria_melody_dataset

- 5 Pop

Each main melody selected by the authors is transformed in several ways, and each class is composed of the original melody and its transformations. More details about this dataset can be found in Table 6.4.

number of classes	30
number of files	3000
files per class distribution	homogeneous (100 files per class)
file format	.flac
duration (mean)	25.84829
duration (std)	6.51136
duration (min)	9.36
duration (max)	37.45

Table 6.4: *Extra information about Panteli’s melody dataset.*

Maria Panteli’s rhythm dataset

The rhythm dataset¹⁶ created by Panteli and Dixon [PD⁺16] is composed of 30 main rhythms divided in six musical styles, as follows:

- monophonic rhythms:
 - 5 Afro-American
 - 5 North-Indian
 - 5 African
 - 5 Classical
- polyphonic rhythms:
 - 5 Electronic Dance Music (EDM)
 - 5 Latin-Brazilian

Similarly to the previous dataset, each original rhythm are subject to various transformations, and each class is formed by the original rhythm and its transformations. Extra information about this dataset is located in Table 6.5.

number of classes	30
number of files	3000
files per class distribution	homogeneous (100 files per class)
file format	.flac
duration (mean)	8.0103
duration (std)	0.51466
duration (min)	6.56
duration (max)	10.0

Table 6.5: *Extra information about Panteli’s rhythm dataset.*

¹⁶https://archive.org/details/panteli_maria_rhythm_dataset

MAST

The MAST¹⁷ dataset is composed of 3721 audio files recorded at several examinations of reproductions of rhythmic patterns performed at a conservatory in Turkey in the years 2005/2006. Besides the identification of the rhythm pattern, each audio file is annotated with one of the 3 labels “reference”, “pass”, or “fail”. The first is the original recording, which was played for the musicians as reference; the second is a recording of an examination in which the musician passed; the third one in which the musician failed.

Since the failed recordings have no use to us, they are dropped. The resulting dataset is classified according to the identification of the rhythm patterns (each class contains the reference recording along with the corresponding recordings of the musicians that passed the exam). Refer to Table 6.6 for further information.

number of classes	40
number of files	3104
files per class distribution	heterogeneous (see Figure 6.3)
file format	.m4a
duration (mean)	4.64725
duration (std)	0.58415
duration (min)	2.41
duration (max)	7.2

Table 6.6: *Extra information about MAST dataset.*

Figure 6.3: *Histogram of files per class from MAST dataset.*

1517-Artists

The 1517-Artists¹⁸ dataset is presented in the PhD thesis by Klaus Seyerlehner [Sey10b]. It is a dataset for musical similarity with 3180 tracks performed by 1517 artists.

In his thesis, Seyerlehner states that a musical recommendation system based on audio similarity can suffer from an artist (or album) effect, in which only the songs by the same artist (or album) of the query song are recommended. In order to avoid this, the 1517-Artists dataset is constructed with just a few tracks by each artist, and is supposed to be used in such a way that no track from the same artist appears in both training and testing sets simultaneously.

¹⁷<https://zenodo.org/record/2620357>

¹⁸http://www.seyerlehner.info/index.php?p=1_3_Download

Even though we do not use this dataset for classification tasks, the 1517-Artists is annotated with musical genres, and so can also be used for timbre similarity. More information can be seen in Table 6.7.

number of classes	19
number of files	3180
files per class distribution	heterogeneous (see Figure 6.4)
file format	.mp3
duration (mean)	233.08766
duration (std)	85.27873
duration (min)	87.75
duration (max)	698.7

Table 6.7: *Extra information about 1517-Artists dataset.*

Figure 6.4: *Histogram of files per class from 1517-Artists dataset.*

MIR-QBSH

The dataset MIR-QBSH¹⁹ was created by the Multimedia Information Retrieval Lab from the National University of Tsing Hua (Taiwan) for the task of query by singing/humming. It consists of 48 MIDI files with the reference melodies and 4431 audio files of these melodies hummed by 195 people.

The dataset went through a process where each MIDI file was synthesized using the FluidSynth²⁰ command line tool. Each reference melody forms a class of files along with their respective hummed versions. More detailed information about this dataset can be seen in Table 6.8.

¹⁹<http://mirlab.org/dataSet/public/MIR-QBSH-corpus.rar>

²⁰<http://www.fluidsynth.org/>

number of classes	48
number of files	4479
files per class distribution	heterogeneous (see Figure 6.5)
file format	.wav
duration (mean)	8.34834
duration (std)	6.46538
duration (min)	8.0
duration (max)	278.07

Table 6.8: *Extra information about MIR-QBSH dataset.*

Figure 6.5: *Histogram of files per class from MIR-QBSH dataset.*

FMA-Small

The Free Music Archive dataset [DBVB17] was published in 2017 with the purpose of evaluating various distinct tasks in Music Information Retrieval (MIR). Its full version has 917Gb comprising 106,574 tracks, all under a Creative-Commons²¹ license.

The version we are using is called FMA-Small²² and is a subset with 8000 files equally divided in 8 musical genres. Detailed information for this dataset is shown in Table 6.9.

number of classes	8
number of files	8000
files per class distribution	homogeneous (1000 files per class)
file format	.mp3
duration (mean)	29.95643
duration (std)	0.51339
duration (min)	6.0
duration (max)	33.24

Table 6.9: *Extra information about FMA-Small dataset.*

²¹<https://creativecommons.org/>

²²<https://github.com/mdeff/fma/>

Covers80

The Covers80 dataset²³ is the first of 5 datasets we use for experiments with the **Cover Song Identification (CSI)** problem, which is a music similarity application selected to further explore the proposed similarity models. It was published in 2007 and is formed by 80 pairs of song/cover, from artists such as Aerosmith, Beatles, Cream, Deep Purple, etc. More details about this dataset can be found in Table 6.10.

number of classes	80
number of files	160
files per class distribution	homogeneous (2 files per class)
file format	.mp3
duration (mean)	250.30606
duration (std)	79.4877
duration (min)	117.83
duration (max)	595.37

Table 6.10: *Extra information about Covers80 dataset.*

YouTubeCovers

The YouTubeCovers²⁴ dataset was released in 2015 and is formed by 350 tracks divided in 50 groups of 7 versions of each original track. Artists appearing in this dataset include Amy Winehouse, Bee Gees, Cake, Daft Punk, among others. Meta-information about the YouTubeCovers dataset can be found in Table 6.11.

number of classes	50
number of files	350
files per class distribution	homogeneous (7 files per class)
file format	.mp3
duration (mean)	263.11166
duration (std)	100.26204
duration (min)	91.9
duration (max)	826.93

Table 6.11: *Extra information about YouTubeCovers dataset.*

Covers1000

The Covers1000 dataset²⁵ was created in 2017 by Christopher Tralie, and is constituted by 395 classes with 2, 3 or 4 cover songs, adding up to 1000 tracks. The author states that the songs were randomly selected from the Second Hand Songs²⁶ website, and later manually curated and checked. From the available meta-data we recognize the presence of similar artists from the two previous datasets. More details can be found in Table 6.6.

²³<https://labrosa.ee.columbia.edu/projects/coversongs/covers80/>

²⁴<https://sites.google.com/site/ismir2015shapelets/data>

²⁵<http://www.covers1000.net/>

²⁶<https://secondhandsongs.com/>

number of classes	395
number of files	1000
files per class distribution	heterogeneous (see Figure 6.6)
file format	659 .ebm (65.9%) / 322 .m4a (32.2%) / 19 .mp3 (1.9%)
duration (mean)	222.32492
duration (std)	87.54064
duration (min)	71.96
duration (max)	927.92

Table 6.12: *Extra information about Covers1000 dataset.*

Figure 6.6: *Histogram of files per class from Covers1000 dataset.*

Mazurkas

The Mazurkas dataset²⁷ is unique among those selected for the CSI experiments. It is composed of several performances of 49 selected Chopin Mazurkas. This dataset is widely known for its continued use in the MIREX Audio Cover Song Identification task²⁸. Further information is shown in Table 6.13.

number of classes	49
number of files	2741
files per class distribution	heterogeneous (see Figure 6.7)
file format	.mp4
duration (mean)	163.75769
duration (std)	74.36453
duration (min)	27.25
duration (max)	487.31

Table 6.13: *Extra information about Mazurkas dataset.*

²⁷<http://www.mazurka.org.uk/>

²⁸https://www.music-ir.org/mirex/wiki/2020:Audio_Cover_Song_Identification

Figure 6.7: Histogram of files per class from Mazurkas dataset.

SHS9K

The dataset we call SHS9K²⁹ is also a selection from the Second Hand Songs massive database. More specifically, it is a sub-set of the SHS100K dataset³⁰ crafted by us by selecting the original songs that have from 50 to 100 covers. This resulted in a new dataset with slightly more than 9000 tracks, hence its name. Detailed information can be found in Table 6.14.

number of classes	143
number of files	9286
files per class distribution	heterogeneous (see Figure 6.8)
file format	7716 .opus (83%) / 1551 .m4a (16%) / 19 .ogg (1%)
duration (mean)	224.4103
duration (std)	101.38956
duration (min)	59.63
duration (max)	2708.61

Table 6.14: Extra information about SHS9K dataset.

²⁹<https://rppbodo.github.io/phd/shs9k.html>

³⁰<https://github.com/NovaFrost/SHS100K>

Figure 6.8: Histogram of files per class from SHS9K dataset.

6.3 Data rearrangement and cleaning

Every dataset we use in our experiments presents issues either with the directories/files hierarchy tree, or with the audio recordings content. Regarding the hierarchy tree, all datasets have been standardized in order to be manipulated by the implemented framework. The final tree structure can be seen in Figure 6.9.

Figure 6.9: Final tree structure after the rearrangement process.

Regarding data cleaning, we had to deal with two main issues. The most common one is the presence of silence in the beginning or end of the file (or both) that takes up a significant fraction of the file duration, as we can see in the example in Figure 6.10. The solution adopted here is to perform a trim on both ends of all tracks.

Figure 6.10: Example recording with presence of silence in the end of the file.

The second issue relates to DC components, which although less frequent, can be more dangerous than the previous issue. Basically, it consists of a vertical shift of the time domain audio signal, sometimes making the amplitude values all above (or below) zero, as shown in Figure 6.11. The solution for this problem is to filter out the DC component by subtracting the mean from all samples.

Figure 6.11: Example recording with vertical shift of the time domain audio signal.

6.4 Experiment #1: Music Similarity

6.4.1 Experiment design

The goal of our first experiment is to check which music similarity models lead to best results for the annotated datasets we selected. In order to accomplish this we run each one of the 9 datasets considered through our music similarity framework, compute the **Intra-Inter Class Similarity Ratio (IICSR)** for every class, and finally compute the weighted mean **IICSR** for each one of the 690 music similarity models considered.

6.4.2 Results

The results are provided for the reader as follows:

- the top-10 weighted mean **IICSR** values for each dataset are presented in this section (Tables 6.15-6.23);
- the best **IICSR** values for each class and dataset are listed in Appendix A;
- the entire list of **IICSR** values computed in this experiment is published in https://rppbodo.github.io/phd/experiment_1.html

Ballroom

weighted mean iicsr	extractor	aggregator	distance
1.3540499634178205	spectral_bandwidth	vector_quantization	cosine_distance
1.3534165441182575	spectral_bandwidth	vector_quantization_default	cosine_distance
1.34745124592136	spectral_rolloff	vector_quantization	cosine_distance
1.3218322081020337	spectral_bandwidth	vector_quantization_default	manhattan_distance
1.3181242579060137	spectral_flatness	vector_quantization_default	manhattan_distance
1.3176688901939193	spectral_rolloff	vector_quantization_default	cosine_distance
1.3162289921171548	spectral_bandwidth	vector_quantization	manhattan_distance
1.3123177903304417	spectral_rolloff	vector_quantization	manhattan_distance
1.30713484050078	spectral_flatness	vector_quantization	manhattan_distance
1.3040807412653603	spectral_flatness	vector_quantization	chebyshev_distance

Table 6.15: The top-10 results for Ballroom dataset.

GTZAN

weighted mean iicsr	extractor	aggregator	distance
1.7494572740656718	spectral_contrast	vector_quantization	cosine_distance
1.7131831605622414	spectral_contrast	vector_quantization_default	cosine_distance
1.6788328390171978	spectral_contrast	vector_quantization	manhattan_distance
1.6759432689949039	spectral_contrast	vector_quantization_default	manhattan_distance
1.418845639658447	spectral_bandwidth	vector_quantization_default	cosine_distance
1.4103487415673173	spectral_bandwidth	vector_quantization	cosine_distance
1.3836662833613098	spectral_bandwidth	vector_quantization	manhattan_distance
1.3812174678017382	spectral_bandwidth	vector_quantization_default	manhattan_distance
1.3581029443038866	spectral_flatness	vector_quantization	manhattan_distance
1.351530977309869	spectral_rolloff	vector_quantization_default	cosine_distance

Table 6.16: The top-10 results for GTZAN dataset.

IOACAS-QBH

weighted mean iicsr	extractor	aggregator	distance
1.092476072741732	pitch_contour_segmentation	octave_abstraction	lcs_circular_min
1.087884691051669	pitch_contour_segmentation	interval_abstraction	lcs_min
1.073704506284947	pitch_contour_segmentation	pitch_contour_5_levels	lcs_min
1.061096398839759	pitch_contour_segmentation	pitch_contour_3_levels	lcs_min
1.0351712811724265	tonnetz	statistical_summarization	cosine_distance
1.023542856425961	chroma_stft	vector_quantization_default	manhattan_distance
1.0221451612555899	chroma_stft	vector_quantization_default	euclidean_distance
1.021471201783239	chroma_stft	vector_quantization_default	cosine_distance
1.020460038429503	beat_synchronous_chroma_stft	vector_quantization_default	manhattan_distance
1.018800012510516	beat_synchronous_chroma_stft	statistical_summarization	chebyshev_distance

Table 6.17: The top-10 results for IOACAS-QBH dataset.

Maria Panteli's melody dataset

weighted mean iicsr	extractor	aggregator	distance
3.121672460498691	pitch_contour_segmentation	interval_abstraction	levenshtein_max
2.8784933361226916	pitch_contour_segmentation	interval_abstraction	lcs_max
2.7668967351583764	melspectrogram	statistical_summarization	cosine_distance
2.7037201080229716	melspectrogram	gaussian_mixture_model_default	cosine_distance
2.506759190743482	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
2.4480779120261142	spectral_contrast	vector_quantization	cosine_distance
2.4177974266180406	pitch_contour_segmentation	interval_abstraction	lcs_mean
2.2584899152688735	mfcc	vector_quantization	manhattan_distance
2.2526835343526903	spectral_contrast	vector_quantization	manhattan_distance
2.2435619283602906	pitch_contour_segmentation	octave_abstraction	lcs_circular_max

Table 6.18: The top-10 results for Maria Panteli's melody dataset.

Maria Panteli's rhythm dataset

weighted mean iicsr	extractor	aggregator	distance
2.8293656707245263	chroma_cens	vector_quantization	manhattan_distance
2.7623598781359173	chroma_cens	vector_quantization	cosine_distance
2.48723963483041	beat_synchronous_chroma_stft	vector_quantization	manhattan_distance
2.393660849090048	beat_synchronous_chroma_cens	vector_quantization	manhattan_distance
2.361307847543314	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
2.345796969404894	beat_synchronous_chroma_cens	vector_quantization	cosine_distance
2.187603115508135	mfcc	vector_quantization	manhattan_distance
2.1371463415826595	beat_synchronous_chroma_cqt	vector_quantization	manhattan_distance
2.1105097583986066	beat_synchronous_chroma_cqt	vector_quantization	cosine_distance
2.0369103515947824	mfcc	vector_quantization	cosine_distance

Table 6.19: The top-10 results for Maria Panteli's rhythm dataset.

MAST

weighted mean iicsr	extractor	aggregator	distance
1.4396680845011323	mfcc	vector_quantization	cosine_distance
1.3125029718125802	mfcc	vector_quantization	manhattan_distance
1.2465251362753116	melspectrogram	vector_quantization	cosine_distance
1.1924435178522057	chroma_cens	vector_quantization	cosine_distance
1.1840461600719778	melspectrogram	vector_quantization	manhattan_distance
1.1729248978438367	beat_synchronous_chroma_cqt	vector_quantization	cosine_distance
1.166218396960286	beat_synchronous_chroma_cens	vector_quantization	cosine_distance
1.1645781941317102	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
1.157322340846282	beat_synchronous_chroma_cqt	vector_quantization	manhattan_distance
1.155902837959492	chroma_cens	vector_quantization	manhattan_distance

Table 6.20: The top-10 results for MAST dataset.

1517-Artists

weighted mean iicsr	extractor	aggregator	distance
1.2055620886915397	mfcc	vector_quantization	cosine_distance
1.176134102621637	mfcc	vector_quantization_default	cosine_distance
1.1568750811844912	spectral_flatness	vector_quantization	manhattan_distance
1.1553044988931647	mfcc	vector_quantization	manhattan_distance
1.1539750706463232	spectral_bandwidth	vector_quantization	cosine_distance
1.1509643592853198	spectral_rolloff	vector_quantization	cosine_distance
1.1500943736026472	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
1.1493571493864683	spectral_bandwidth	vector_quantization_default	cosine_distance
1.1486351584539187	spectral_rolloff	vector_quantization_default	cosine_distance
1.1464940564416854	mfcc	vector_quantization_default	manhattan_distance

Table 6.21: The top-10 results for 1517-Artists dataset.

MIR-QBSH

weighted mean iicsr	extractor	aggregator	distance
1.2949131442350692	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
1.2402936615590263	pitch_contour_segmentation	interval_abstraction	levenshtein_max
1.233022209189783	pitch_contour_segmentation	octave_abstraction	lcs_circular_min
1.2061107813026728	pitch_contour_segmentation	octave_abstraction	lcs_circular_max
1.2047184610592656	pitch_contour_segmentation	pitch_contour_5_levels	levenshtein_max
1.1796156638383086	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean
1.177118878994491	pitch_contour_segmentation	interval_abstraction	lcs_max
1.1764569956217827	pitch_contour_segmentation	pitch_contour_3_levels	levenshtein_max
1.1623291012208554	pitch_contour_segmentation	pitch_contour_5_levels	lcs_max
1.1582764726064485	pitch_contour_segmentation	markov_chain	circular_cosine

Table 6.22: The top-10 results for MIR-QBSH dataset.

FMA-Small

weighted mean iicsr	extractor	aggregator	distance
1.2112879995990873	mfcc	vector_quantization_default	cosine_distance
1.2074322324746771	mfcc	vector_quantization	cosine_distance
1.1839280987042582	mfcc	vector_quantization	manhattan_distance
1.1824114904970324	mfcc	vector_quantization_default	manhattan_distance
1.1775203487886956	melspectrogram	statistical_summarization	cosine_distance
1.1552211718086771	spectral_bandwidth	vector_quantization_default	cosine_distance
1.1520489565884702	spectral_rolloff	vector_quantization	cosine_distance
1.1484443004872782	spectral_bandwidth	vector_quantization	cosine_distance
1.1480826442713625	spectral_rolloff	vector_quantization_default	cosine_distance
1.147194473827082	spectral_rolloff	vector_quantization	manhattan_distance

Table 6.23: The top-10 results for FMA-Small dataset.

6.4.3 Discussion

Melodic, Rhythmic and Genre datasets

Three of the datasets considered are aimed specifically to test melodic similarity models: MIQ-QBSH and IOACAS-QBH are designed for the query-by-humming task (classes are composed of a reference melody and a set of recordings of people trying to hum it), and Panteli’s melody dataset uses synthesis to test similarity models against several melodic transformations. The models that achieved the best weighted mean **IICSR** are:

- $\{pitch_contour_segmentation, octave_abstraction, levenshtein_circular_max\}$ for MIQ-QBSH;
- $\{pitch_contour_segmentation, octave_abstraction, lcs_circular_min\}$ for IOACAS-QBH;
- $\{pitch_contour_segmentation, interval_abstraction, levenshtein_max\}$ for Panteli’s melody dataset.

All of the models above have Pitch Contour Segmentation as their feature, which matches the hypothesis that melodic features lead to better results for melodic datasets. Regarding the aggregators we have two models using octave abstraction and one using interval abstraction. This is somehow expected, since the alternatives – 3-level and 5-level pitch contours – are relatively weaker due to their simplistic representations of the original pitch sequences.

Three other datasets – Ballroom, MAST and Panteli’s rhythm dataset – are designed for tasks related to rhythm similarity. The first one is composed of recordings from distinct dance styles; the second one has recordings of students successfully reproducing rhythmic patterns; the later is composed of different rhythms under several transformations. The best models for each dataset are:

- $\{spectral_bandwidth, vector_quantization, cosine_distance\}$ for Ballroom;
- $\{mfcc, vector_quantization, cosine_distance\}$ for MAST;
- $\{chroma_cens, vector_quantization, manhattan_distance\}$ for Panteli’s rhythm dataset.

The models that performed best for these datasets are relatively surprising, not only because none of the features are specifically designed for rhythm similarity tasks, but also because they are very different from each other: Spectral Bandwidth is related to the spectrum spread, MFCC is usually associated with timbre, and Chroma Energy Normalized Statistics (CENS) is a tonal feature.

The three remaining datasets – GTZAN, 1517-Artists, FMA-Small – are annotated with the tracks’ genres. As discussed before, several papers in the literature claim that there is a relationship between genre and timbre, and under this assumption, these datasets could be used to test timbre similarity models. The highest weighted mean IICSR are obtained with the following models:

- $\{spectral_contrast, vector_quantization, cosine_distance\}$ for GTZAN;
- $\{mfcc, vector_quantization, cosine_distance\}$ for 1517-Artists;
- $\{mfcc, vector_quantization_default, cosine_distance\}$ for FMA-Small.

Two out of the three best models mentioned above have MFCC as their feature, and the other one has Spectral Contrast. MFCC is a feature usually related to timbre, so this matches the initial hypothesis. According to Jiang et al. [JLZ⁺02], Spectral Contrast is reported to have a better discriminating power for different music types than MFCC, so it is noteworthy that this feature has also emerged here.

Results per class

Next we analyse the IICSR for each individual class, according to the results presented in Appendix A.

Starting with the melodic datasets, MIR-QBSH has 26 classes (melodies) out of 48 ($\approx 54\%$) whose best model is $\{pitch_contour_segmentation, octave_abstraction, levenshtein_circular_max\}$, followed by $\{pitch_contour_segmentation, interval_abstraction, levenshtein_max\}$ for 9 classes ($\approx 18\%$). The model that appear more frequently (28 classes out of 298 - $\approx 9\%$) for IOACAS-QBH is $\{pitch_contour_segmentation, interval_abstraction, lcs_min\}$, technically tied with $\{mfcc, vector_quantization, cosine_distance\}$ which is best for 27 classes ($\approx 9\%$). For Panteli’s melody dataset the first model is $\{pitch_contour_segmentation, interval_abstraction, levenshtein_max\}$, which is best for 10 out of 30 classes ($\approx 33\%$), and the second best is $\{melspectrogram, statistical_summarization, cosine_distance\}$ (for 6 out of 30 classes, or 20%).

The observations here are quite similar to the ones referring to the weighted mean IICSR, where we are mainly concerned to check if the types of features appearing in the best models matches the tasks for which the datasets were designed. In this case, the datasets designed for melodic tasks produce best results (for most classes) using models with Pitch Contour Segmentation as feature, but noteworthy exceptions are MFCC with IOACAS-QBH and melspectrogram with Panteli’s dataset.

For the rhythmic datasets, Ballroom has the model $\{spectral_rolloff, vector_quantization, cosine_distance\}$, with 2 classes (dance types) out of 10 (20%), tied with $\{spectral_flatness, diff_stats_2, chebyshev_distance\}$ (also 2 classes or 20%). MAST has 32 classes (rhythmic patterns) out of 40

(80%) whose best model is $\{mfcc, vector_quantization, cosine_distance\}$, followed by $\{melspectrogram, vector_quantization, cosine_distance\}$ which is best for 5 classes (12.5%). Panteli’s rhythm dataset has 11 out of 30 classes ($\approx 36\%$) with best model being $\{chroma_cens, vector_quantization, cosine_distance\}$, and the second best model $\{chroma_cens, vector_quantization, manhattan_distance\}$, for 7 classes of 30 ($\approx 23\%$).

The rhythmic datasets best models per class followed nearly the same pattern as when analysing the weighted mean **IICSR** values: the Ballroom dataset presents spectral features as the most frequent, 80% of the classes from MAST dataset have the best model using **MFCC** as feature, and Panteli’s rhythm dataset has the **CENS** feature as the most frequent, considering the number of classes for which it appears in the best models.

The genre (or timbre) datasets have the following best models, when analysing the individual classes. GTZAN has in first place $\{spectral_contrast, vector_quantization, cosine_distance\}$ for 4 classes out of 10 (40%), and in second place $\{melspectrogram, gaussian_mixture_model_default, cosine_distance\}$ for 2 classes out of 10 (20%). 1517-Artists has the best model $\{melspectrogram, gaussian_mixture_model_default, cosine_distance\}$ for 6 out of 19 classes ($\approx 31\%$), followed by $\{temporal_statistical_spectrum_descriptor, bypass, cosine_distance\}$ for 4 out of 19 classes ($\approx 21\%$). The FMA-Small dataset has as best models $\{mfcc, vector_quantization_default, cosine_distance\}$ for 2 classes out of 8 (25%), tied with $\{melspectrogram, gaussian_mixture_model_default, cosine_distance\}$ also for 2 classes out of 8 (25%).

Some remarkable results appear with the genre datasets in the above analysis. Besides the already expected models, which have timbre (or other spectral) features as their first element, some distinct models appeared here for the first time. For instance, Temporal Statistical Spectrum Descriptor shows up as the feature for the second most frequent model for 1517-Artists dataset. This is roughly a rhythmic feature, and this finding suggests an alternative approach to distinguish genres by music perspectives other than timbre.

We also would like to register that the model that leads to the best weighted mean **IICSR** for a dataset is not necessarily the most frequent model when counting the best models for individual classes. For instance, the best model in average for 1517-Artists has **MFCC** as its feature, while the most frequent models have melspectrogram and Temporal Statistical Spectrum Descriptor as their features, for $\approx 31\%$ and $\approx 21\%$ of the classes respectively.

Comparative analysis

Next we present a comparative analysis of the results, considering **IICSR** values obtained from very similar models (considering variations of specific details).

Several models include features which may or may not be synchronized to the beats. According to Table 6.24, the synchronized models achieved a slightly higher average performance, i.e., the highest mean value of **IICSR** over all 9 datasets.

beat-synchronous?	weighted mean iicr (mean)	weighted mean iicr (std)
yes	1.0613942664419753	0.13502158454978952
no	1.054403957112558	0.11633719623232362

Table 6.24: Average results for models that do or do not use beat-synchronous features.

Table 6.25 compares models that apply (or not) the **Optimal Transposition Index (OTI)**. Results are marginally better when **OTI** is applied.

OTI applied?	weighted mean iicr (mean)	weighted mean iicr (std)
yes	1.0453967661190973	0.06992686333055692
no	1.0446341713815084	0.06949308225223967

Table 6.25: Average results for models that do or do not use OTI.

As seen in Section 2.3, LCS-based distances are computed by dividing the length of the **Longest Common Subsequence (LCS)** by three alternatives values: the minimum, mean and maximum of the lengths of the two sequences being compared. Table 6.26 shows that the best average result is obtained by dividing the **LCS**-length to the maximum, although the spread of the **IICSR** values is larger; the smaller spread occurs using the minimum as denominator, but this also produces the smaller weighted mean **IICSR**.

function used	weighted mean iicr (mean)	weighted mean iicr (std)
min	1.062289167637259	0.17594215851354272
mean	1.1209214132881897	0.28139660828286006
max	1.1724594908899157	0.3824835767516491

Table 6.26: Average results for models using minimum, mean or maximum to compute LCS-based distances.

The same comparison can be made for the models that use the Levenshtein distance to compare two symbolic melodic sequences. As Table 6.27 shows, the highest average result across all datasets is obtained using the maximum of the sequences lengths, but again the spread is much worse in this case.

function used	weighted mean iicr (mean)	weighted mean iicr (std)
min	1.0022681075684954	0.006668255790810766
mean	1.071226607689819	0.15633168399303013
max	1.1824659151025125	0.43507425892616736

Table 6.27: Average results for models that use minimum, mean or maximum to compute Levenshtein distances.

When aggregating local features into global ones using single Gaussian models we used a few alternative versions. As seen in Section 2.2, the method called *basic_stats_1* is composed of the mean and standard deviation values of each dimension of the local feature; *basic_stats_2* is *basic_stats_1* with added minimum and maximum values for each dimension; *diff_stats_1* is *basic_stats_1* concatenated with mean and standard deviation values of the difference of the features in each dimension; and *diff_stats_2* is obtained from *diff_stats_1* by adding the minimum and maximum values from both the feature sequence and its difference.

aggregator	weighted mean iicr (mean)	weighted mean iicr (std)
basic_stats_1	1.0442789316659908	0.07682125963980427
basic_stats_2	1.0430074642691964	0.08077065712859963
diff_stats_1	1.0467260309527056	0.07955852655272544
diff_stats_2	1.0428426784620992	0.08511169059676862

Table 6.28: Average results for models that use the four variations of single Gaussian as aggregation model.

From Table 6.28 we verify that *basic_stats_2* has worst mean result than *basic_stats_1* and *diff_stats_2* has worse mean result than *diff_stats_1*, so we can conclude that, for the models and datasets experimented, adding minimum and maximum values does not help. Comparing *basic_stats_1* with *diff_stats_1* we verify that the use of extra information regarding the difference of the features leads to slightly improved results.

All model using vector quantization as aggregation method was used in the experiment with the default number of clusters, and also with one cluster per class (as discussed in Section 2.2). Table 6.29 shows that using the default values leads to worst results, so the proposed idea of matching the number of clusters with the number of classes appears to be worth it (although the spread becomes larger).

number of clusters	weighted mean iicsr (mean)	weighted mean iicsr (std)
number of classes	1.1562207356318348	0.27738676416067043
function default (8)	1.1198686700737968	0.17850814034079127

Table 6.29: Average results for vector quantization models using default or tailored number of clusters.

The last comparative analysis is related to features implemented by the *RP_extract* module. Some of the features are provided with statistical summarization over time, besides the regular version. We can verify in Table 6.30 that the regular versions yield marginally better results for the datasets considered in the experiment.

temporal features?	weighted mean iicsr (mean)	weighted mean iicsr (std)
yes	1.0597115107027533	0.1332907243029386
no	1.0612171968855186	0.08395955789035918

Table 6.30: Average results for models with or without temporal summarization.

6.5 Experiment #2: Cover Song Identification

6.5.1 Experiment design

This experiment has a similar goal to the previous one, namely to check which music similarity models lead to best results, but now with *CSI* datasets. We compute similarity matrices using all 690 models for all 5 *CSI* datasets, and then calculate metrics which are specific to this problem: Mean Rank (MR), Mean Reciprocal Rank (MRR), Median Rank (MDR), Mean Average Precision (MAP), etc.

6.5.2 Results

The results are displayed in the following manner:

- the top-10 models for each dataset are presented in Tables 6.31 to 6.35, which are broken in two parts because they do not fit horizontally on the pages (please use line id as guidance);
- the top-50 models for each dataset are listed in Appendix B;
- the entire list of metrics computed in this experiment is published in https://rppbodo.github.io/phd/experiment_2.html

Covers80

line id	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
1	41.575	0.19359	31.0	0.19359	21.0	46.0	142.0	160.0
2	41.99375	0.19206	32.0	0.19206	20.0	44.0	142.0	160.0
3	42.3625	0.20598	27.5	0.20598	20.0	56.0	138.0	160.0
4	42.44375	0.1901	24.0	0.1901	18.0	57.0	141.0	160.0
5	42.4625	0.18129	32.0	0.18129	19.0	47.0	143.0	160.0
6	42.675	0.19459	24.0	0.19459	19.0	57.0	136.0	160.0
7	42.71875	0.17317	31.0	0.17317	18.0	46.0	142.0	160.0
8	43.01875	0.18078	34.0	0.18078	17.0	48.0	136.0	160.0
9	43.08125	0.20681	25.0	0.20681	23.0	48.0	137.0	160.0
10	43.35625	0.16701	29.5	0.16701	16.0	46.0	137.0	160.0

(a)

line id	extractor	aggregator	distance
1	chroma_stft	diff_stats_1	cosine_distance_oti
2	chroma_stft	basic_stats_1	cosine_distance_oti
3	beat_synchronous_chroma_cens	basic_stats_2	manhattan_distance_oti
4	beat_synchronous_chroma_cens	basic_stats_2	euclidean_distance_oti
5	chroma_stft	diff_stats_1	manhattan_distance_oti
6	beat_synchronous_chroma_cens	basic_stats_2	cosine_distance_oti
7	chroma_stft	statistical_summarization	manhattan_distance_oti
8	chroma_stft	diff_stats_1	euclidean_distance_oti
9	chroma_stft	statistical_summarization	cosine_distance_oti
10	chroma_stft	basic_stats_2	chebyshev_distance_oti

(b)

Table 6.31: *The top-10 results for Covers80 dataset.***YouTubeCovers**

line id	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
1	7.97143	0.6942	1.0	0.36114	219.0	296.0	345.0	350.0
2	9.41143	0.63231	1.0	0.2977	189.0	279.0	345.0	350.0
3	14.1	0.4344	3.5	0.19221	110.0	231.0	343.0	350.0
4	14.13714	0.40846	5.0	0.1805	103.0	233.0	344.0	350.0
5	14.71143	0.38021	5.0	0.15415	85.0	227.0	344.0	350.0
6	15.89429	0.37811	5.0	0.15807	93.0	216.0	346.0	350.0
7	15.89429	0.37811	5.0	0.15807	93.0	216.0	346.0	350.0
8	16.46286	0.37605	5.5	0.15219	86.0	223.0	343.0	350.0
9	16.85429	0.5271	2.0	0.21466	153.0	247.0	335.0	350.0
10	17.06	0.35579	6.0	0.14139	78.0	225.0	342.0	350.0

(a)

line id	extractor	aggregator	distance
1	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean
2	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
3	pitch_contour_segmentation	markov_chain	circular_manhattan
4	pitch_contour_segmentation	markov_chain	circular_cosine
5	chroma_stft	statistical_summarization	cosine_distance_oti
6	pitch_contour_segmentation	markov_chain	circular_euclidean
7	pitch_contour_segmentation	markov_chain	circular_chebyshev
8	chroma_stft	diff_stats_1	cosine_distance_oti
9	pitch_contour_segmentation	octave_abstraction	lcs_circular_max
10	chroma_stft	basic_stats_1	cosine_distance_oti

(b)

Table 6.32: *The top-10 results for YouTubeCovers dataset.*

Covers1000

line id	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
1	144.041	0.25731	35.0	0.19159	201.0	366.0	636.0	1000.0
2	175.546	0.09845	74.5	0.06977	52.0	188.0	548.0	1000.0
3	180.808	0.13566	75.0	0.09752	77.0	249.0	551.0	1000.0
4	181.48	0.15934	72.0	0.11552	103.0	261.0	558.0	1000.0
5	183.802	0.0861	95.0	0.06054	48.0	155.0	515.0	1000.0
6	184.645	0.12143	81.0	0.08497	70.0	213.0	533.0	1000.0
7	185.462	0.13359	79.0	0.09661	80.0	236.0	540.0	1000.0
8	185.521	0.14401	84.5	0.10473	93.0	228.0	525.0	1000.0
9	185.781	0.09549	97.0	0.06776	49.0	183.0	512.0	1000.0
10	185.884	0.14356	86.0	0.10421	93.0	229.0	526.0	1000.0

(a)

line id	extractor	aggregator	distance
1	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean
2	beat_synchronous_chroma_stft	diff_stats_1	cosine_distance_oti
3	beat_synchronous_chroma_cqt	diff_stats_1	manhattan_distance_oti
4	rhythm_histogram	bypass	cosine_distance
5	beat_synchronous_chroma_stft	basic_stats_1	cosine_distance_oti
6	chroma_cens	basic_stats_2	manhattan_distance_oti
7	beat_synchronous_chroma_cqt	diff_stats_1	euclidean_distance_oti
8	beat_synchronous_chroma_cens	diff_stats_1	cosine_distance_oti
9	beat_synchronous_chroma_stft	diff_stats_1	manhattan_distance_oti
10	beat_synchronous_chroma_cens	diff_stats_1	euclidean_distance_oti

(b)

Table 6.33: The top-10 results for Covers1000 dataset.

Mazurkas

line id	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
1	4.15724	0.95774	1.0	0.82286	2561.0	2714.0	2728.0	2739.0
2	4.46479	0.87347	1.0	0.33623	2251.0	2638.0	2722.0	2740.0
3	4.6297	0.83039	1.0	0.28564	2076.0	2620.0	2721.0	2740.0
4	4.65268	0.85999	1.0	0.32391	2197.0	2622.0	2717.0	2741.0
5	4.86173	0.8785	1.0	0.3994	2241.0	2671.0	2718.0	2741.0
6	4.86647	0.83115	1.0	0.30325	2067.0	2615.0	2723.0	2739.0
7	4.95659	0.81238	1.0	0.24961	2018.0	2583.0	2722.0	2740.0
8	4.9865	0.80264	1.0	0.2673	1965.0	2593.0	2726.0	2741.0
9	5.08063	0.95648	1.0	0.86734	2551.0	2713.0	2728.0	2737.0
10	5.14447	0.79237	1.0	0.30303	1921.0	2602.0	2722.0	2741.0

(a)

line id	extractor	aggregator	distance
1	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
2	beat_synchronous_chroma_cqt	statistical_summarization	manhattan_distance_oti
3	chroma_cqt	statistical_summarization	manhattan_distance_oti
4	beat_synchronous_chroma_cens	statistical_summarization	manhattan_distance_oti
5	beat_synchronous_chroma_stft	statistical_summarization	manhattan_distance_oti
6	beat_synchronous_chroma_cens	diff_stats_2	manhattan_distance_oti
7	chroma_stft	statistical_summarization	manhattan_distance_oti
8	chroma_stft	statistical_summarization	cosine_distance_oti
9	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean
10	chroma_stft	diff_stats_1	cosine_distance_oti

(b)

Table 6.34: The top-10 results for Mazurkas dataset.

SHS9K

line id	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
1	47.57883	0.40387	6.0	0.05102	3008.0	5188.0	8067.0	9265.0
2	56.67866	0.33549	11.0	0.03429	2385.0	4527.0	7741.0	9273.0
3	59.06128	0.31115	13.0	0.02701	2182.0	4334.0	7658.0	9272.0
4	62.9398	0.23255	15.0	0.02777	1275.0	3990.0	7836.0	9240.0
5	63.73713	0.22736	16.0	0.02813	1234.0	3914.0	7809.0	9238.0
6	64.75038	0.22813	16.0	0.02696	1265.0	3888.0	7787.0	9237.0
7	65.22755	0.22587	16.0	0.02669	1222.0	3899.0	7766.0	9236.0
8	65.88273	0.18724	20.0	0.02269	927.0	3407.0	7716.0	9243.0
9	66.06203	0.29483	16.0	0.02617	2038.0	4100.0	7485.0	9270.0
10	66.90114	0.18625	20.0	0.02065	903.0	3429.0	7646.0	9252.0

(a)

line id	extractor	aggregator	distance
1	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean
2	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
3	pitch_contour_segmentation	octave_abstraction	lcs_circular_max
4	beat_synchronous_chroma_cqt	diff_stats_1	manhattan_distance_oti
5	beat_synchronous_chroma_cqt	diff_stats_1	cosine_distance_oti
6	beat_synchronous_chroma_cqt	statistical_summarization	manhattan_distance_oti
7	beat_synchronous_chroma_cqt	diff_stats_1	euclidean_distance_oti
8	beat_synchronous_chroma_cqt	diff_stats_2	manhattan_distance_oti
9	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_mean
10	beat_synchronous_chroma_stft	diff_stats_1	manhattan_distance_oti

(b)

Table 6.35: *The top-10 results for SHS9K dataset.***6.5.3 Discussion****Best results**

The models that result in the best mean rank values for the **CSI** datasets are shown in Table 6.36. Four models out of five share the same feature (pitch_contour_segmentation) and the same aggregator (octave_abstraction), which is a very good indication of the relevance of these methods for **CSI**, while the remaining model uses a chromagram as feature. All features appearing in the best models encode tonal information, which corroborates the observation in the literature that tonal differences are less frequent between versions of the same song [SGH10, SSG12, CLX17].

dataset	extractor	aggregator	distance
Covers80	chroma_stft	diff_stats_1	cosine_distance_oti
YouTubeCovers	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean
Covers1000	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean
Mazurkas	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
SHS9K	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean

Table 6.36: *The best results for Experiment #2.*

Moreover, if we analyse the Top-50 list of best features for each dataset (see Appendix B) we may verify that 249 models out of 250 (99.6%) use tonal features: 231 models use Chromagrams, 17 models use Pitch Contour Segmentation, and 1 model uses Tonnetz. This is a stronger evidence that tonal similarity has indeed the highest relevance for the **CSI** problem. As a side note, the only model that doesn't include a tonal feature is $\{rhythm_histogram, bypass, cosine_distance\}$, the fourth best model for Covers1000, which uses a rhythmic feature.

Comparative results

As seen in the comparative analysis of Experiment #1, some techniques may differ by only a single setting, for instance, models that share the same feature, aggregator, and distance, but where the feature is beat-synchronized in one model and not in the other. Similarly to what was done in the preceding section, we analyse which settings are best, but now for **CSI** datasets.

Comparing models that may (or not) use beat-synchronous features, we can verify (see Table 6.37) that in average it is better not to beat-sync features for the **CSI** datasets and the models we included in the experiment.

beat-synchronous?	mean rank (mean)	mean rank (std)
yes	89.3480537370109	172.35261733957287
no	88.3282453970704	90.53508052977543

Table 6.37: Average results for models that do or do not use beat-synchronous features.

According to Table 6.38 we conclude that applying OTI leads to better results for the models and datasets compared.

OTI applied?	mean rank (mean)	mean rank (std)
yes	82.69112416120925	192.75918501547838
no	85.20164733110768	84.94848924394955

Table 6.38: Average results for models that do or do not use OTI.

When computing the LCS-based distances, the best results are obtained using the mean length for normalisation, as shown in Table 6.39.

function used	mean rank (mean)	mean rank (std)
min	321.7782208039525	314.83518453601465
mean	105.87476892655063	110.58916821207373
max	108.87226174873874	105.8208158479763

Table 6.39: Average results for models using minimum, mean or maximum to normalise LCS-based distances.

Table 6.40 shows that better results can be achieved by using the mean length for normalisation when computing Levenshtein distances.

function used	mean rank (mean)	mean rank (std)
min	104.611049187205	92.176838784475
mean	100.96905325877044	91.34877090282131
max	109.92441834426197	105.13459286919078

Table 6.40: Average results for models that use minimum, mean or maximum to normalise Levenshtein distances.

As explained in Section 2.2, we compare several distinct aggregators based on the single Gaussian model. Comparing the average mean ranks in Table 6.41 we may verify that, in average, *basic_stats_1* is better than *basic_stats_2*, and *diff_stats_1* is better than both *diff_stats_2* and *basic_stats_1*. Thereby we can conclude that adding the minimum and maximum values to the global features is not worth it, and that it is beneficial to add information about the feature differences to the global features.

aggregator	mean rank (mean)	mean rank (std)
basic_stats_1	95.26268075728171	92.57033667079618
basic_stats_2	99.63181852081064	98.3795194071255
diff_stats_1	93.58111901686559	91.45156497941215
diff_stats_2	118.82704802637727	232.48864683342376

Table 6.41: Average results for models that use the four variations of single Gaussian as aggregation model.

As we can see in Table 6.42, for the CSI datasets, the models that use vector quantization as aggregation method lead to better results with the default number of clusters³¹.

³¹<https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html>

number of clusters	mean rank (mean)	mean rank (std)
number of classes	118.19316996341703	260.85976735055647
function default (8)	106.07161721064126	97.17924297824821

Table 6.42: Average results for vector quantization models using default or tailored number of clusters.

Finally, when comparing features from the *RP_extract* library that have temporal summarization as an option, it is better not to use it according to Table 6.43.

temporal features?	mean rank (mean)	mean rank (std)
yes	113.86163326823744	102.01929218250392
no	104.53442949216674	89.31943704335092

Table 6.43: Average results for models with or without temporal summarization.

Analysing these comparative results from the *CSI* datasets with those of Experiment #1, we can verify what both experiments have in common: we should apply *OTI* to chromagrams, not add minimum and maximum values to single Gaussian aggregators, consider the feature differences for single Gaussian aggregators, and avoid temporal features when using the *RP_extract* library.

comparative analysis	music similarity	cover song identification
beat-synchronous?	yes	no
OTI applied?	yes	yes
LCS function	max	mean
Levenshtein function	max	mean
add min and max to Gaussian aggregator?	no	no
add diff to Gaussian aggregator?	yes	yes
number of clusters (vector quantization)	number of classes	function default
temporal features?	no	no

Table 6.44: Comparative results for Music Similarity versus Cover Song Identification datasets.

6.6 Experiment #3: Cover Song Classification

6.6.1 Experiment design

The main goal of Experiment #3 is to explore different sample definitions, i.e. different ways to combine similarity models, for the *Cover Song Classification (CSC)* problem and verify which model combinations lead to the best results. As explained in Section 5.2, we consider two alternative approaches: fusing models using the Top-N best models (N equals to 10, 20, 30, 40, and 50), and using the filtered list of models (skipping so-called “equivalent” ones). We are going to refer to these alternatives as Experiments #3a and #3b.

In both experiments we use samples from the same dataset to train and test classifiers, setting split percentages to 70/30. Since our samples share information of pairs of songs, and a song that appears in the train set cannot appear again in the test set, we apply a heuristic (as described in Section 5.2) to separate classes of tracks.

We use five classifiers (Naive Bayes, Logistic Regression, Decision Tree, Random Forest, and Ada Boost), run each configuration 10 times to make good use of the random splits, and compute mean and standard deviation of every classification metric (f-score, precision, recall, accuracy, 0’s accuracy, and 1’s accuracy).

The best results by dataset are presented below and, for consultation, we present the Top-50 models per dataset in Appendix B and the filtered models per dataset in Appendix C. Also, all classification results are published in https://rppbodo.github.io/phd/experiment_3.html.

6.6.2 Results: experiment #3a

In Experiment #3a we build tensors using the Top-N best models, so the dimension of the samples is defined by the number of models we use. Since we have 5 classifiers, 5 different N values, and 10 different splits for each setting, we have 250 classification runs in total. Tables 6.45-6.49 display the best 10 results for each 5 CSI datasets.

Covers80

line id	dimension	classifier	f1-score (mean)	f1-score (std)	precision (mean)	precision (std)	recall (mean)	recall (std)
1	30	random_forest	0.70751	0.01326	0.9702	0.03995	0.55781	0.02102
2	50	random_forest	0.70083	0.01211	0.98122	0.02956	0.54531	0.01094
3	10	random_forest	0.69955	0.01926	0.96295	0.029	0.55	0.024
4	40	random_forest	0.69906	0.01882	0.96491	0.02663	0.54844	0.02031
5	30	ada_boost	0.69254	0.02162	0.9151	0.06552	0.55937	0.02688
6	20	random_forest	0.69068	0.0211	0.97847	0.0327	0.53438	0.024
7	50	ada_boost	0.6875	0.02586	0.92149	0.03513	0.54844	0.02259
8	40	ada_boost	0.68512	0.03228	0.91654	0.07159	0.54844	0.02747
9	20	ada_boost	0.68185	0.02352	0.94547	0.05262	0.53438	0.02596
10	10	ada_boost	0.68101	0.03351	0.9071	0.08111	0.54688	0.0221

(a)

line id	accuracy (mean)	accuracy (std)	0's acc. (mean)	0's acc. (std)	1's acc. (mean)	1's acc. (std)
1	0.9856	0.00063	0.9994	0.00084	0.55781	0.02102
2	0.98545	0.00065	0.99965	0.00055	0.54531	0.01094
3	0.98525	0.00078	0.99929	0.00056	0.55	0.024
4	0.98525	0.00084	0.99934	0.00051	0.54844	0.02031
5	0.98447	0.00134	0.99819	0.00155	0.55937	0.02688
6	0.98506	0.00091	0.9996	0.00063	0.53438	0.024
7	0.98442	0.00126	0.99849	0.00068	0.54844	0.02259
8	0.98423	0.00181	0.99829	0.0015	0.54844	0.02747
9	0.98442	0.00119	0.99894	0.00104	0.53438	0.02596
10	0.98394	0.00216	0.99803	0.00196	0.54688	0.0221

(b)

Table 6.45: Top-10 results for Covers80 in Experiment #3a of CSC.

YouTubeCovers

line id	dimension	classifier	f1-score (mean)	f1-score (std)	precision (mean)	precision (std)	recall (mean)	recall (std)
1	40	ada_boost	0.48029	0.02518	0.82439	0.05955	0.3402	0.02604
2	40	random_forest	0.47871	0.02079	0.88495	0.07285	0.32959	0.02162
3	20	random_forest	0.47015	0.03995	0.89132	0.04495	0.32122	0.0398
4	10	random_forest	0.46446	0.03359	0.82369	0.056	0.32571	0.03643
5	20	ada_boost	0.46408	0.03529	0.84501	0.02923	0.32122	0.03496
6	30	random_forest	0.45923	0.0365	0.8269	0.10298	0.32571	0.05414
7	50	ada_boost	0.4587	0.02132	0.81802	0.07667	0.32	0.01843
8	50	random_forest	0.45395	0.0256	0.90094	0.04924	0.30449	0.02484
9	10	ada_boost	0.45043	0.03082	0.82771	0.077	0.31163	0.03201
10	30	ada_boost	0.44774	0.03767	0.75775	0.09581	0.32531	0.05271

(a)

line id	accuracy (mean)	accuracy (std)	0's acc. (mean)	0's acc. (std)	1's acc. (mean)	1's acc. (std)
1	0.96326	0.00152	0.99605	0.00161	0.3402	0.02604
2	0.96414	0.00167	0.99754	0.00203	0.32959	0.02162
3	0.96401	0.00157	0.99784	0.0011	0.32122	0.0398
4	0.96263	0.00132	0.99615	0.00163	0.32571	0.03643
5	0.96307	0.00137	0.99685	0.00085	0.32122	0.03496
6	0.96207	0.00188	0.99556	0.00425	0.32571	0.05414
7	0.96223	0.00204	0.99604	0.0022	0.32	0.01843
8	0.96346	0.00114	0.99814	0.00121	0.30449	0.02484
9	0.96211	0.00165	0.99635	0.00194	0.31163	0.03201
10	0.96029	0.00228	0.99371	0.00434	0.32531	0.05271

(b)

Table 6.46: Top-10 results for YouTubeCovers in Experiment #3a of CSC.

Covers1000

line id	dimension	classifier	f1-score (mean)	f1-score (std)	precision (mean)	precision (std)	recall (mean)	recall (std)
1	10	random_forest	0.57966	0.00478	0.96275	0.01583	0.4148	0.0074
2	10	ada_boost	0.5781	0.01072	0.96817	0.01531	0.41221	0.0111
3	20	ada_boost	0.57484	0.00896	0.95694	0.02049	0.41092	0.0082
4	20	random_forest	0.5726	0.00714	0.97836	0.01466	0.40481	0.00712
5	50	ada_boost	0.5724	0.00794	0.95081	0.01816	0.40962	0.00945
6	30	ada_boost	0.57194	0.01057	0.96565	0.02579	0.40648	0.01023
7	40	random_forest	0.57154	0.00576	0.97678	0.01609	0.40407	0.00728
8	40	ada_boost	0.5713	0.01368	0.9643	0.02279	0.40629	0.01622
9	50	random_forest	0.56818	0.00629	0.97666	0.01953	0.40074	0.0069
10	30	random_forest	0.56739	0.0063	0.98546	0.01738	0.39852	0.00783

(a)

line id	accuracy (mean)	accuracy (std)	0's acc. (mean)	0's acc. (std)	1's acc. (mean)	1's acc. (std)
1	0.99583	2e-05	0.99989	5e-05	0.4148	0.0074
2	0.99583	8e-05	0.9999	5e-05	0.41221	0.0111
3	0.99579	9e-05	0.99987	6e-05	0.41092	0.0082
4	0.99581	6e-05	0.99994	4e-05	0.40481	0.00712
5	0.99576	6e-05	0.99985	6e-05	0.40962	0.00945
6	0.99579	0.0001	0.9999	8e-05	0.40648	0.01023
7	0.9958	4e-05	0.99993	5e-05	0.40407	0.00728
8	0.99578	8e-05	0.99989	8e-05	0.40629	0.01622
9	0.99578	6e-05	0.99993	6e-05	0.40074	0.0069
10	0.99579	4e-05	0.99996	5e-05	0.39852	0.00783

(b)

Table 6.47: *Top-10 results for Covers1000 in Experiment #3a of CSC.***Mazurkas**

line id	dimension	classifier	f1-score (mean)	f1-score (std)	precision (mean)	precision (std)	recall (mean)	recall (std)
1	50	random_forest	0.91457	0.0134	0.97536	0.01013	0.86116	0.02086
2	30	random_forest	0.90372	0.01394	0.96467	0.01556	0.85021	0.0178
3	40	random_forest	0.90307	0.01612	0.95885	0.02565	0.85384	0.01811
4	50	logistic_regression	0.90007	0.01664	0.98039	0.00913	0.83225	0.02584
5	20	random_forest	0.89885	0.00701	0.95285	0.0121	0.85084	0.01191
6	10	random_forest	0.89372	0.01176	0.95761	0.03267	0.83897	0.02123
7	40	logistic_regression	0.88701	0.01165	0.97486	0.02065	0.8142	0.01902
8	30	logistic_regression	0.88592	0.01386	0.97366	0.01337	0.81297	0.02066
9	20	logistic_regression	0.88552	0.00725	0.96497	0.01052	0.81837	0.01374
10	20	ada_boost	0.87581	0.00976	0.94003	0.01046	0.81997	0.01491

(a)

line id	accuracy (mean)	accuracy (std)	0's acc. (mean)	0's acc. (std)	1's acc. (mean)	1's acc. (std)
1	0.99123	0.0013	0.99874	0.00052	0.86116	0.02086
2	0.99012	0.0014	0.9982	0.00082	0.85021	0.0178
3	0.98998	0.00171	0.99785	0.00139	0.85384	0.01811
4	0.98993	0.00156	0.99904	0.00045	0.83225	0.02584
5	0.98957	0.0007	0.99757	0.00066	0.85084	0.01191
6	0.98911	0.00132	0.99777	0.00185	0.83897	0.02123
7	0.98867	0.00114	0.99876	0.00106	0.8142	0.01902
8	0.98858	0.00131	0.99872	0.00066	0.81297	0.02066
9	0.98848	0.00068	0.99828	0.00054	0.81837	0.01374
10	0.98734	0.00094	0.99698	0.00056	0.81997	0.01491

(b)

Table 6.48: *Top-10 results for Mazurkas in Experiment #3a of CSC.*

SHS9K

line id	dimension	classifier	f1-score (mean)	f1-score (std)	precision (mean)	precision (std)	recall (mean)	recall (std)
1	20	naive_bayes	0.08792	0.00458	0.0552	0.00446	0.22045	0.01992
2	40	decision_tree	0.06982	0.00294	0.07181	0.00344	0.06796	0.0028
3	50	decision_tree	0.06968	0.00206	0.07229	0.00157	0.06732	0.00317
4	30	naive_bayes	0.06761	0.00601	0.03701	0.00396	0.40306	0.03381
5	30	decision_tree	0.06549	0.00131	0.06812	0.00184	0.06308	0.00157
6	20	decision_tree	0.06516	0.00164	0.0691	0.00192	0.06169	0.00212
7	10	decision_tree	0.06183	0.0018	0.06799	0.00133	0.05673	0.00234
8	40	naive_bayes	0.06097	0.00397	0.03252	0.00236	0.496	0.02807
9	50	naive_bayes	0.05754	0.00376	0.03046	0.00221	0.52758	0.0276
10	10	naive_bayes	0.05038	0.00253	0.05069	0.00389	0.05028	0.00267

(a)

line id	accuracy (mean)	accuracy (std)	0's acc. (mean)	0's acc. (std)	1's acc. (mean)	1's acc. (std)
1	0.91604	0.01183	0.92896	0.0124	0.22045	0.01992
2	0.96698	0.00051	0.98368	0.00052	0.06796	0.0028
3	0.96724	0.00065	0.98395	0.00071	0.06732	0.00317
4	0.79433	0.03371	0.80159	0.03496	0.40306	0.03381
5	0.96719	0.00052	0.98397	0.00055	0.06308	0.00157
6	0.96774	0.00056	0.98456	0.0006	0.06169	0.00212
7	0.96863	0.0004	0.98556	0.00045	0.05673	0.00234
8	0.71927	0.03408	0.72341	0.03521	0.496	0.02807
9	0.68257	0.0359	0.68545	0.03707	0.52758	0.0276
10	0.96542	0.00161	0.98241	0.00166	0.05028	0.00267

(b)

Table 6.49: Top-10 results for SHS9K in Experiment #3a of CSC.

6.6.3 Discussion: experiment #3a

Best results

The best results for Covers80 are obtained using random forest classifier with Top-30 models; for YouTubeCovers these are obtained using ada boost with Top-40 models; for Covers1000 these are obtained using random forest with Top-10 models; for Mazurkas these are obtained using random forest with Top-50 models; for SHS9K these are obtained using naive Bayes with Top-20 models.

Comparing the mean f1-score of these results, Mazurkas achieves the highest score for the CSC problem (as for the CSI problem) with f1=0.91457. This dataset is mainly composed of piano recordings which have more potential to generate cleaner tonal features (such as chromagrams) and better automatic transcriptions (as with Pitch Contour Segmentation). Following Mazurkas, the datasets along with the best mean f1-scores achieved are Covers80 (f1=0.70751), Covers1000 (f1=0.57966), YouTubeCovers (f1=0.48029), and SHS9K (f1=0.08792) which is by far the most difficult dataset in the context of this experiment.

Recalling the CSI results, we had the following Mean Ranks: Mazurkas (with MR=4.15724), YouTubeCovers (MR=7.97143), Covers80 (MR=41.575), SHS9K (MR=47.57883), and Covers1000 (MR=144.041). We should notice two datasets in particular: Covers1000 achieved bad results in the CSI problem, but considerably good results in the CSC, while for SHS9K we observed the opposite performance of our models in the CSI and CSC problems.

Comparative results

Figure 6.12: Summarized results to experiment #3a by dimension (a) and by classifier (b).

Analyzing Figure 6.12a, which resumes all the classification runs according to the dimension of the Top-N models, we can see a slightly higher mean f1-score for the Top-10 models. Moreover, it does not present any evidence that using more models yields better results. One plausible reason for this is the fact that, even though the larger Top-N lists do include more information about the pair of songs, the models added are very similar to the previous ones, so they do not actually help the classification process. As discussed before, from the Top-50 models of the 5 CSI datasets, there are 231 models with chromagrams as features, 17 models with Pitch Contour Segmentation, and 1 model with tonnetz, so most models can be seen as variations of the topmost models.

Figure 6.12b shows all the results according to the classifier used. Random forest and ada boost have the best results (random forest is the classifier with the best results for Covers80, Covers1000, and Mazurkas; ada boost is the classifier with the best result for YouTubeCovers). These classifiers are followed by logistic regression, decision tree, and naive Bayes, in this order.

6.6.4 Results: experiment #3b

In Experiment #3b we build tensors using the filtered models (see Section 5.2), exploring the individual models as well as all combinations of models in pairs and in groups of three. This is done in order to exploit distinct information obtained by fusing different models. The sample dimension is defined by the number of models (1–3) in each combination, and the number of settings is determined by the number of combinations. The model filtering process leads to lists of 16 models, so adding up 16, 120 (number of combinations of size 2), and 560 (number of combinations of size 3) we obtain 696 in total. Multiplying it by 5 classifiers and 10 different splits, we have in total 34,800 classification runs. Tables 6.50–6.54 show the best 10 results for all datasets.

Covers80

line id	length	models	classifier
1	3	{chroma_stft, diff_stats_1, cosine_distance_oti}	naive_bayes
2	3	{chroma_stft, basic_stats_1, cosine_distance_oti} {beat_synchronous_chroma_cens, basic_stats_2, manhattan_distance_oti}	random_forest
3	2	{beat_synchronous_chroma_cens, statistical_summarization_2, monte_carlo_distance} {pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
4	3	{chroma_stft, basic_stats_1, cosine_distance_oti}	random_forest
5	3	{beat_synchronous_chroma_cens, basic_stats_2, manhattan_distance_oti} {beat_synchronous_chroma_cens, statistical_summarization_2, monte_carlo_distance}	random_forest
6	3	{chroma_cqt, vector_quantization_default, cosine_distance} {pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	naive_bayes
7	3	{chroma_stft, diff_stats_1, cosine_distance_oti} {beat_synchronous_chroma_cens, basic_stats_2, manhattan_distance_oti}	random_forest
8	3	{chroma_cqt, vector_quantization_default, cosine_distance} {beat_synchronous_chroma_cens, basic_stats_2, manhattan_distance_oti}	random_forest
9	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean} {mfcc, statistical_summarization_2, monte_carlo_distance}	random_forest
10	3	{beat_synchronous_chroma_cens, statistical_summarization_2, monte_carlo_distance} {pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	naive_bayes

(a)

line id	f1-score (mean)	f1-score (std)	precision (mean)	precision (std)	recall (mean)	recall (std)
1	0.70709	0.01742	0.97635	0.03197	0.55469	0.01881
2	0.70106	0.0267	0.95889	0.03469	0.55312	0.02856
3	0.7003	0.01416	0.94322	0.04184	0.55781	0.01888
4	0.69998	0.01896	0.97792	0.02491	0.54531	0.01907
5	0.69993	0.01439	0.97907	0.02973	0.54531	0.02031
6	0.69949	0.01787	0.99744	0.00769	0.53906	0.02344
7	0.69888	0.02203	0.96329	0.03483	0.54922	0.02685
8	0.69735	0.0173	0.97277	0.02978	0.54375	0.01646
9	0.69716	0.01778	0.96221	0.02964	0.54688	0.01712
10	0.69635	0.01549	1.0	0.0	0.53438	0.01822

(b)

line id	accuracy (mean)	accuracy (std)	0's acc. (mean)	0's acc. (std)	1's acc. (mean)	1's acc. (std)
1	0.98564	0.00082	0.99955	0.00062	0.55469	0.01881
2	0.98528	0.00119	0.99922	0.00067	0.55312	0.02856
3	0.98508	0.00075	0.99887	0.00086	0.55781	0.01888
4	0.9854	0.00085	0.9996	0.00045	0.54531	0.01907
5	0.9854	0.0006	0.9996	0.00059	0.54531	0.02031
6	0.98555	0.00063	0.99995	0.00015	0.53906	0.02344
7	0.98523	0.00097	0.99929	0.0007	0.54922	0.02685
8	0.98525	0.00083	0.9995	0.00056	0.54375	0.01646
9	0.98516	0.00085	0.99929	0.00056	0.54688	0.01712
10	0.98545	0.00057	1.0	0.0	0.53438	0.01822

(c)

Table 6.50: Top-10 results for Covers80 in Experiment #3b of the CSC problem.

YouTubeCovers

line id	length	models	classifier
1	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
2	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
3	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
4	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
5	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	ada_boost
6	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
7	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	ada_boost
8	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
9	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	ada_boost
10	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	ada_boost

(a)

line id	f1-score (mean)	f1-score (std)	precision (mean)	precision (std)	recall (mean)	recall (std)
1	0.48576	0.02425	0.82668	0.07015	0.34643	0.02989
2	0.47995	0.02784	0.83543	0.05175	0.33796	0.02815
3	0.47957	0.02361	0.82868	0.04793	0.33827	0.02356
4	0.47918	0.02456	0.79661	0.11895	0.34806	0.02965
5	0.47338	0.02846	0.86892	0.05007	0.32694	0.03034
6	0.47238	0.0278	0.81299	0.06603	0.33449	0.02685
7	0.46963	0.03598	0.87965	0.05308	0.32184	0.03395
8	0.46948	0.03245	0.83914	0.05695	0.32694	0.02979
9	0.46847	0.03373	0.86959	0.04984	0.32153	0.03039
10	0.46778	0.03173	0.86596	0.06568	0.32194	0.03107

(b)

line id	accuracy (mean)	accuracy (std)	0's acc. (mean)	0's acc. (std)	1's acc. (mean)	1's acc. (std)
1	0.96342	0.00161	0.9959	0.00237	0.34643	0.02989
2	0.96347	0.00147	0.99639	0.0014	0.33796	0.02815
3	0.96334	0.00144	0.99624	0.0013	0.33827	0.02356
4	0.96214	0.00368	0.99446	0.00475	0.34806	0.02965
5	0.96376	0.00116	0.99727	0.00138	0.32694	0.03034
6	0.96269	0.00206	0.99576	0.00212	0.33449	0.02685
7	0.9638	0.00168	0.99758	0.00132	0.32184	0.03395
8	0.96314	0.00181	0.99663	0.0013	0.32694	0.02979
9	0.96362	0.00175	0.99741	0.00107	0.32153	0.03039
10	0.96347	0.00187	0.99723	0.00165	0.32194	0.03107

(c)

Table 6.51: Top-10 results for YouTubeCovers in Experiment #3b of the CSC problem.

Covers1000

line id	length	models	classifier
1	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
2	3	{rhythm_histogram, bypass, cosine_distance}	random_forest
3	3	{tonnetz, diff_stats_1, manhattan_distance}	random_forest
4	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
5	3	{rhythm_histogram, bypass, cosine_distance}	random_forest
6	3	{beat_synchronous_chroma_cens, statistical_summarization_2, monte_carlo_distance}	random_forest
7	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
8	3	{rhythm_histogram, bypass, cosine_distance}	random_forest
9	3	{beat_synchronous_chroma_stft, vector_quantization, manhattan_distance}	random_forest
10	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
		{beat_synchronous_chroma_cqt, diff_stats_1, manhattan_distance_oti}	
		{rhythm_histogram, bypass, cosine_distance}	
		{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	
		{beat_synchronous_chroma_stft, vector_quantization, manhattan_distance}	
		{beat_synchronous_chroma_cens, statistical_summarization_2, monte_carlo_distance}	
		{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	
		{rhythm_histogram, bypass, cosine_distance}	
		{pitch_contour_segmentation, markov_chain, circular_manhattan}	
		{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	
		{beat_synchronous_chroma_stft, diff_stats_1, cosine_distance_oti}	
		{beat_synchronous_chroma_cens, statistical_summarization_2, monte_carlo_distance}	
		{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	
		{beat_synchronous_chroma_cens, statistical_summarization_2, monte_carlo_distance}	
		{temporal_rhythm_histogram, bypass, cosine_distance}	
		{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	
		{beat_synchronous_chroma_cens, statistical_summarization_2, monte_carlo_distance}	
		{pitch_contour_segmentation, markov_chain, circular_manhattan}	
		{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	
		{tonnetz, diff_stats_1, manhattan_distance}	
		{beat_synchronous_chroma_cens, statistical_summarization_2, monte_carlo_distance}	

(a)

line id	f1-score (mean)	f1-score (std)	precision (mean)	precision (std)	recall (mean)	recall (std)
1	0.58666	0.00989	0.95689	0.01797	0.42313	0.00992
2	0.58364	0.00708	0.95884	0.01848	0.41961	0.00768
3	0.57913	0.00747	0.95357	0.01372	0.41591	0.00749
4	0.57452	0.00856	0.94528	0.01711	0.41277	0.00845
5	0.57434	0.00804	0.94644	0.01512	0.4123	0.00682
6	0.57396	0.00833	0.9579	0.0173	0.40981	0.00745
7	0.57353	0.00933	0.95497	0.02364	0.4099	0.00685
8	0.57296	0.00671	0.95172	0.022	0.40999	0.00714
9	0.57287	0.00614	0.96514	0.01853	0.4074	0.00594
10	0.57223	0.00807	0.93664	0.02649	0.41221	0.00975

(b)

line id	accuracy (mean)	accuracy (std)	0's acc. (mean)	0's acc. (std)	1's acc. (mean)	1's acc. (std)
1	0.99587	8e-05	0.99987	6e-05	0.42313	0.00992
2	0.99585	6e-05	0.99987	6e-05	0.41961	0.00768
3	0.99581	6e-05	0.99986	4e-05	0.41591	0.00749
4	0.99576	7e-05	0.99983	6e-05	0.41277	0.00845
5	0.99577	8e-05	0.99984	5e-05	0.4123	0.00682
6	0.99579	8e-05	0.99987	5e-05	0.40981	0.00745
7	0.99578	0.0001	0.99986	7e-05	0.4099	0.00685
8	0.99577	7e-05	0.99985	7e-05	0.40999	0.00714
9	0.99579	6e-05	0.9999	6e-05	0.4074	0.00594
10	0.99573	8e-05	0.9998	9e-05	0.41221	0.00975

(c)

Table 6.52: Top-10 results for Covers1000 in Experiment #3b of the CSC problem.

Mazurkas

line id	length	models	classifier
1	3	{pitch_contour_segmentation, octave_abstraction, levenshtein_circular_max}	random_forest
2	3	{pitch_contour_segmentation, markov_chain, circular_manhattan} {chroma_cens, statistical_summarization_2, monte_carlo_distance}	random_forest
3	3	{pitch_contour_segmentation, octave_abstraction, levenshtein_circular_max} {chroma_cens, statistical_summarization_2, monte_carlo_distance}	random_forest
4	3	{pitch_contour_segmentation, octave_abstraction, levenshtein_circular_max} {chroma_cens, statistical_summarization_2, monte_carlo_distance}	random_forest
5	3	{pitch_contour_segmentation, octave_abstraction, levenshtein_circular_max} {chroma_cens, gaussian_mixture_model_default, manhattan_distance}	random_forest
6	3	{pitch_contour_segmentation, octave_abstraction, levenshtein_circular_max} {chroma_cens, statistical_summarization_2, monte_carlo_distance}	random_forest
7	3	{pitch_contour_segmentation, octave_abstraction, levenshtein_circular_max} {chroma_cens, statistical_summarization_2, monte_carlo_distance}	random_forest
8	3	{pitch_contour_segmentation, octave_abstraction, levenshtein_circular_max} {chroma_cens, statistical_summarization_2, monte_carlo_distance}	random_forest
9	3	{pitch_contour_segmentation, octave_abstraction, levenshtein_circular_max} {chroma_cens, statistical_summarization_2, monte_carlo_distance}	random_forest
10	3	{pitch_contour_segmentation, octave_abstraction, levenshtein_circular_max} {beat_synchronous_chroma_cqt, vector_quantization, chebyshev_distance}	random_forest

(a)

line id	f1-score (mean)	f1-score (std)	precision (mean)	precision (std)	recall (mean)	recall (std)
1	0.89848	0.00728	0.9499	0.0107	0.85271	0.01768
2	0.8952	0.00805	0.96593	0.01266	0.83441	0.01543
3	0.89085	0.01256	0.95649	0.01063	0.83421	0.02521
4	0.89037	0.01264	0.94522	0.0259	0.84251	0.02438
5	0.89035	0.01204	0.96719	0.01589	0.82545	0.02453
6	0.88954	0.01124	0.94116	0.03692	0.84437	0.01174
7	0.88855	0.00354	0.96728	0.02177	0.82233	0.01641
8	0.88799	0.01225	0.96704	0.01977	0.82169	0.02575
9	0.88669	0.01444	0.97294	0.01948	0.81595	0.036
10	0.88258	0.01713	0.96247	0.03001	0.81592	0.0263

(b)

line id	accuracy (mean)	accuracy (std)	0's acc. (mean)	0's acc. (std)	1's acc. (mean)	1's acc. (std)
1	0.98953	0.00066	0.9974	0.00061	0.85271	0.01768
2	0.98936	0.00075	0.99829	0.00065	0.83441	0.01543
3	0.98888	0.00111	0.9978	0.0006	0.83421	0.02521
4	0.98871	0.00127	0.99713	0.00144	0.84251	0.02438
5	0.9889	0.00112	0.99836	0.00084	0.82545	0.02453
6	0.98857	0.00143	0.99686	0.00208	0.84437	0.01174
7	0.98873	0.0004	0.99835	0.00115	0.82233	0.01641
8	0.9887	0.00113	0.99835	0.00108	0.82169	0.02575
9	0.98866	0.00117	0.99864	0.00104	0.81595	0.036
10	0.98815	0.00172	0.9981	0.00162	0.81592	0.0263

(c)

Table 6.53: Top-10 results for Mazurkas in Experiment #3b of the CSC problem.

SHS9K

Experiments for the dataset SHS9K are in progress. Table 6.54 shows the best results obtained with $\approx 20\%$ of the classification runs obtained so far.

line id	length	models	classifier
1	2	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	naive_bayes
2	2	{beat_synchronous_chroma_cqt, statistical_summarization_2, monte_carlo_distance}	naive_bayes
3	2	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	naive_bayes
4	2	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	naive_bayes
5	2	{beat_synchronous_chroma_cqt, diff_stats_1, manhattan_distance_oti}	naive_bayes
6	2	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	naive_bayes
7	2	{beat_synchronous_chroma_cqt, diff_stats_1, cosine_distance_oti}	naive_bayes
8	2	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	naive_bayes
9	2	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	naive_bayes
10	2	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	naive_bayes

(a)

line id	f1-score (mean)	f1-score (std)	precision (mean)	precision (std)	recall (mean)	recall (std)
1	0.03317	0.00072	0.04586	0.00341	0.02612	0.00142
2	0.03303	0.00086	0.05709	0.00898	0.02356	0.00167
3	0.03247	0.00074	0.05777	0.00834	0.02285	0.00161
4	0.03236	0.00087	0.05597	0.00989	0.02325	0.00232
5	0.03233	0.00063	0.05248	0.00527	0.02351	0.00112
6	0.03212	0.00056	0.0532	0.00374	0.02309	0.00102
7	0.03209	0.00035	0.0535	0.00954	0.02334	0.00173
8	0.03175	0.00053	0.05119	0.00642	0.02326	0.00148
9	0.03158	0.00052	0.05863	0.00926	0.02187	0.00126
10	0.03147	0.00064	0.05412	0.00733	0.02246	0.00176

(b)

line id	accuracy (mean)	accuracy (std)	0's acc. (mean)	0's acc. (std)	1's acc. (mean)	1's acc. (std)
1	0.97224	0.00127	0.98981	0.00132	0.02612	0.00142
2	0.97486	0.00154	0.99253	0.0016	0.02356	0.00167
3	0.97519	0.00137	0.99288	0.00142	0.02285	0.00161
4	0.97468	0.00204	0.99235	0.00212	0.02325	0.00232
5	0.97435	0.00106	0.99201	0.0011	0.02351	0.00112
6	0.97464	0.00079	0.99231	0.00083	0.02309	0.00102
7	0.97435	0.00179	0.992	0.00186	0.02334	0.00173
8	0.97413	0.00161	0.99179	0.00167	0.02326	0.00148
9	0.97554	0.00144	0.99325	0.0015	0.02187	0.00126
10	0.97481	0.0016	0.99249	0.00166	0.02246	0.00176

(c)

Table 6.54: Top-10 results for SHS9K in Experiment #3b of the CSC problem.

6.6.5 Discussion: experiment #3b

Best results

The best results obtained in experiment #3b are as follows: mean f1-score=0.89848 for the Mazurkas dataset using random forest; f1=0.70709 for Covers80 using naive Bayes; f1=0.58666 for Covers1000 using random forest; f1=0.48576 for YouTubeCovers using random forest, all obtained with 3 fused models. Inspecting the models that are fused, we find two models for Mazurkas using Pitch Contour Segmentation and the third with **CENS**; all three models for Covers80 use chromagrams; models for Covers1000 use Pitch Contour Segmentation, Rhythm Histogram and Tonnetz; models for YouTubeCovers use Pitch Contour Segmentation, Rhythm Histogram and **CENS**.

The models for Covers1000 and YouTubeCovers are very unique since they blend tonal features of two different types with a rhythmic feature. Consulting Appendix C we can further observe that the model that uses Rhythm Histogram is the fourth in the list of best models for Covers1000, while the next model using Rhythm Histogram appears as the 53rd in the list for YouTubeCovers. Two conclusions may be drawn from these observations: features that are not tonal as well as features that are not necessarily high ranked may produce good results for the **CSC** problem. This is a point in favor of using the proposed filtered models for **CSC**.

Comparative results

Figure 6.13: Results for experiment #3b, summarized by dimension (a) and by classifier (b).

Figure 6.13a shows us a summarization of all classification results by dimension, i.e., the number of models fused. It is clear that the mean (or median) f1-score increases for larger dimensions, which underlines the relevance of the proposed filtered models. The results summarized by classifier are shown in Figure 6.13b, and again both random forest and ada boost appear as the best classifiers. Comparing it with Experiment #3a, the most prominent difference is observed with logistic regression, which was the third best in the previous experiment, but now dropped to the last position alongside naive bayes.

dataset	best mean f1-score (experiment #3a)	best mean f1-score (experiment #3b)
Covers80	0.70751	0.70709
YouTubeCovers	0.48029	0.48576
Covers1000	0.57966	0.58666
Mazurkas	0.91457	0.89848
SHS9K	0.08792	0.03317

Table 6.55: Best mean f1-score for all datasets in experiments #3a and #3b.

Finally, we also compare experiments #3a and #3b in terms of their best results. Table 6.55 highlights the best mean f1-score for all datasets in both experiments (considering the partial results for SHS9K). These results are quite similar, indicating that the two approaches to fuse models (using plain Top-N lists or filtering out equivalent models) are equally promising. However, fused models in experiment #3b use samples with much smaller dimensions, another finding that favors the use of filtered models. Considering that we stop the combination of models at length 3, and larger dimension values (4, 5, etc) can still be tested, we strongly recommend skipping equivalent models, instead of using the original Top-N lists, in the process of fusing similarity models within the CSC problem.

6.7 Experiment #4: Cover Song Identification and Classification

6.7.1 Experiment design

This experiment exploits the CSC problem in order to return to the CSI problem. Every trained classifier can return values between 0 and 1 (corresponding to a likelihood of a pair of songs being versions) instead of values equal to 0 or 1 (that say if the pair of songs are versions of each other

or not). By gathering this information for all possible pairs of songs from a dataset it is possible to build a brand new similarity matrix, and compute novel CSI metrics. Considering that, the main goal of Experiment #4 is to check if we can get better CSI results using the matrices manufactured by CSC runs.

The classification settings are very similar to the ones in experiment #3, with the following important differences: cross-dataset classification is performed, an unique list of music similarity models is created, and the train sets are balanced to have the same number of 0's and 1's samples (all details are explained in Section 5.2). Moreover, since it is a good practice in machine learning to have the train set larger than the test set, we only consider pairs of datasets for experiment #4 when the train dataset has more tracks than the test dataset, as listed below:

test dataset	train datasets
Covers80	YouTubeCovers; Covers1000; Mazurkas; SHS9K
YouTubeCovers	Covers1000; Mazurkas; SHS9K
Covers1000	Mazurkas; SHS9K
Mazurkas	SHS9K

Table 6.56: *List of all considered train and test datasets for Experiment #4.*

Experiment #4 is also divided in two: #4a uses the Top-N best models (N equals to 10, 20, 30, 40, and 50), and #4b uses the filtered models. From Table 6.56 it is possible to count 10 pairs of classification datasets. This makes experiment #4 ten times larger than experiment #3. Experiment #4a has 10 pairs of datasets, 5 classifiers, 5 dimension values, 10 sample batches randomly varying the 0's samples, resulting in 2,500 classifications runs. Experiment #4b has 10 pairs of datasets, 5 classifiers, 696 possible combinations of filtered models to produce the samples, 10 random batches of samples, resulting in 348,000 classifications runs.

This Section shows the Top-10 results for each dataset, Appendix D shows the unique Top-50 list, and Appendix E the unique filtered list. The entire list of classification results is published in https://rppbodo.github.io/phd/experiment_4.html.

6.7.2 Results: experiment #4a

Covers80

line id	train dataset	dimension	classifier	MR (mean)	MR (std)	MRR (mean)	MRR (std)
1	covers1000	50	naive_bayes	33.97812	0.06698	0.28545	0.00179
2	covers1000	40	naive_bayes	34.64375	0.03412	0.27822	0.00269
3	youtubecovers	40	naive_bayes	34.93875	0.16623	0.27856	0.00232
4	youtubecovers	50	naive_bayes	34.98062	0.46308	0.27935	0.00601
5	youtubecovers	10	naive_bayes	35.1275	0.03793	0.24055	0.00157
6	covers1000	50	logistic_regression	35.18938	0.199	0.28261	0.00346
7	covers1000	30	naive_bayes	35.34	0.03625	0.25136	0.00262
8	youtubecovers	30	naive_bayes	35.57625	0.32109	0.2622	0.00379
9	shs9k	50	naive_bayes	35.7075	0.02179	0.24941	0.00033
10	shs9k	40	naive_bayes	35.77813	0.02742	0.24354	0.00202

(a)

line id	MDR (mean)	MDR (std)	MAP (mean)	MAP (std)	Top-1 (mean)	Top-1 (std)
1	16.25	0.51235	0.28545	0.00179	34.8	0.6
2	16.15	0.22913	0.27822	0.00269	33.8	0.87178
3	16.1	0.3	0.27856	0.00232	33.5	0.67082
4	17.15	0.50249	0.27935	0.00601	31.9	1.13578
5	18.1	0.4899	0.24055	0.00157	26.6	0.4899
6	14.25	1.00623	0.28261	0.00346	34.1	0.83066
7	17.0	0.0	0.25136	0.00262	29.2	0.6
8	15.55	0.41533	0.2622	0.00379	30.8	0.9798
9	18.3	0.24495	0.24941	0.00033	29.0	0.0
10	18.1	0.43589	0.24354	0.00202	28.3	0.45826

(b)

line id	Top-10 (mean)	Top-10 (std)	Top-100 (mean)	Top-100 (std)	Top-1000 (mean)	Top-1000 (std)
1	62.8	0.4	145.0	0.0	160.0	0.0
2	59.0	0.0	145.0	0.0	160.0	0.0
3	62.7	0.64031	143.7	1.00499	160.0	0.0
4	63.0	1.61245	144.0	1.09545	160.0	0.0
5	63.0	0.89443	141.7	0.9	160.0	0.0
6	72.5	1.62788	141.1	1.04403	160.0	0.0
7	61.0	0.44721	144.7	0.45826	160.0	0.0
8	61.0	0.63246	141.7	0.64031	160.0	0.0
9	59.1	0.3	145.0	0.0	160.0	0.0
10	56.7	0.78102	145.0	0.0	160.0	0.0

(c)

Table 6.57: Top-10 results for Covers80 to Experiment #4a.

YouTubeCovers

line id	train dataset	dimension	classifier	MR (mean)	MR (std)	MRR (mean)	MRR (std)
1	covers1000	40	naive_bayes	13.42257	0.04173	0.50354	0.00152
2	covers1000	50	naive_bayes	13.79743	0.03304	0.48866	0.00165
3	mazurkas	20	ada_boost	13.85914	0.35326	0.44791	0.01374
4	covers1000	30	naive_bayes	14.01743	0.02389	0.49034	0.00194
5	mazurkas	20	random_forest	14.04343	0.33195	0.44897	0.01022
6	covers1000	40	logistic_regression	14.11686	0.19979	0.49318	0.00408
7	shs9k	40	naive_bayes	14.16543	0.01763	0.48278	0.00059
8	shs9k	50	naive_bayes	14.20629	0.02359	0.47954	0.00077
9	covers1000	40	random_forest	14.20857	0.80384	0.48012	0.01119
10	shs9k	30	naive_bayes	14.46914	0.02324	0.47304	0.00011

(a)

line id	MDR (mean)	MDR (std)	MAP (mean)	MAP (std)	Top-1 (mean)	Top-1 (std)
1	3.0	0.0	0.21716	0.00041	138.4	1.11355
2	3.0	0.0	0.21384	0.00047	132.2	1.32665
3	3.7	0.45826	0.19596	0.00404	115.5	7.76209
4	3.0	0.0	0.20772	0.00058	134.9	0.9434
5	3.7	0.45826	0.1939	0.00261	115.6	4.84149
6	3.0	0.0	0.2188	0.00245	136.5	2.15639
7	3.4	0.2	0.20693	0.00017	133.1	0.3
8	3.0	0.0	0.20695	0.00016	130.0	0.0
9	3.15	0.32016	0.202	0.00441	131.4	5.55338
10	4.0	0.0	0.19993	0.0001	130.0	0.0

(b)

line id	Top-10 (mean)	Top-10 (std)	Top-100 (mean)	Top-100 (std)	Top-1000 (mean)	Top-1000 (std)
1	258.9	0.53852	345.0	0.0	350.0	0.0
2	254.3	1.9	343.9	0.3	350.0	0.0
3	242.4	3.72022	343.9	1.22066	350.0	0.0
4	252.6	1.35647	343.7	0.64031	350.0	0.0
5	239.0	5.76194	344.4	1.35647	350.0	0.0
6	245.4	2.2	344.3	0.78102	350.0	0.0
7	249.0	0.0	344.0	0.44721	350.0	0.0
8	249.8	0.4	344.0	0.0	350.0	0.0
9	243.6	6.43739	342.2	1.66132	350.0	0.0
10	244.1	0.3	342.0	0.0	350.0	0.0

(c)

Table 6.58: Top-10 results for YouTubeCovers to Experiment #4a.

Covers1000

line id	train dataset	dimension	classifier	MR (mean)	MR (std)	MRR (mean)	MRR (std)
1	shs9k	50	naive_bayes	146.5084	0.06913	0.17431	0.00068
2	shs9k	40	naive_bayes	148.0769	0.07151	0.18237	0.00046
3	mazurkas	20	logistic_regression	151.2592	0.24362	0.14936	0.00092
4	shs9k	30	naive_bayes	152.7983	0.05249	0.17726	0.00013
5	mazurkas	20	ada_boost	155.75	1.88268	0.13797	0.00617
6	mazurkas	20	random_forest	158.4418	2.60728	0.11805	0.00392
7	shs9k	20	naive_bayes	158.8768	0.09422	0.15025	0.00019
8	mazurkas	10	ada_boost	162.3155	2.08897	0.13362	0.00717
9	shs9k	10	naive_bayes	164.3159	0.04239	0.1561	0.00027
10	mazurkas	10	logistic_regression	164.5202	0.08982	0.14963	0.00048

(a)

line id	MDR (mean)	MDR (std)	MAP (mean)	MAP (std)	Top-1 (mean)	Top-1 (std)
1	42.35	0.32016	0.12918	0.00042	103.9	1.51327
2	46.1	0.2	0.13363	0.00031	120.2	0.6
3	59.85	0.22913	0.10694	0.00074	85.7	1.18743
4	55.55	0.15	0.12952	6e-05	121.0	0.0
5	60.35	3.42819	0.09908	0.00631	76.6	8.45222
6	65.55	2.8058	0.08357	0.00413	60.4	4.75815
7	64.1	0.43589	0.10734	0.0001	96.9	0.3
8	69.15	3.3989	0.09524	0.00476	73.5	6.97496
9	59.4	0.3	0.11227	0.00025	100.8	0.4
10	68.0	0.54772	0.11009	0.0004	95.1	0.7

(b)

line id	Top-10 (mean)	Top-10 (std)	Top-100 (mean)	Top-100 (std)	Top-1000 (mean)	Top-1000 (std)
1	311.0	0.44721	615.2	0.6	1000.0	0.0
2	295.9	1.22066	619.8	1.249	1000.0	0.0
3	270.3	0.78102	599.5	1.28452	1000.0	0.0
4	288.9	0.3	592.3	0.45826	1000.0	0.0
5	261.8	8.61162	597.6	6.46838	1000.0	0.0
6	223.8	5.86174	584.6	8.89044	1000.0	0.0
7	267.5	0.5	591.6	0.8	1000.0	0.0
8	244.9	8.45518	578.6	6.28013	1000.0	0.0
9	258.2	0.6	595.4	0.66332	1000.0	0.0
10	250.6	1.49666	571.2	1.46969	1000.0	0.0

(c)

Table 6.59: Top-10 results for Covers1000 to Experiment #4a.

Mazurkas

line id	train dataset	dimension	classifier	MR (mean)	MR (std)	MRR (mean)	MRR (std)
1	shs9k	40	naive_bayes	3.99186	0.01127	0.92073	0.00125
2	shs9k	50	naive_bayes	4.06895	0.01931	0.91092	0.00295
3	shs9k	30	naive_bayes	4.06899	0.00264	0.91694	0.00033
4	shs9k	20	naive_bayes	4.34174	0.00247	0.88371	0.00031
5	shs9k	10	naive_bayes	4.3483	0.00235	0.87817	0.00021
6	shs9k	10	ada_boost	16.28179	2.61392	0.7186	0.01662
7	shs9k	50	random_forest	27.99208	6.54633	0.23056	0.02339
8	shs9k	40	random_forest	32.92525	6.68131	0.20585	0.02657
9	shs9k	10	logistic_regression	37.11022	0.9395	0.26813	0.00619
10	shs9k	10	random_forest	38.40423	13.84079	0.17541	0.03637

(a)

line id	MDR (mean)	MDR (std)	MAP (mean)	MAP (std)	Top-1 (mean)	Top-1 (std)
1	1.0	0.0	0.44795	0.00135	2419.5	5.55428
2	1.0	0.0	0.46185	0.00172	2380.7	12.9387
3	1.0	0.0	0.42365	0.0004	2405.8	1.66132
4	1.0	0.0	0.37273	0.00028	2277.8	1.53623
5	1.0	0.0	0.36039	0.0007	2254.8	1.249
6	1.0	0.0	0.15394	0.00788	1807.6	43.26708
7	14.3	3.68917	0.04349	0.00431	371.2	38.98153
8	17.1	3.93573	0.04268	0.00495	323.7	50.68343
9	10.6	0.4899	0.08062	0.00195	424.2	11.94822
10	22.3	9.74731	0.04108	0.00572	253.3	61.62637

(b)

line id	Top-10 (mean)	Top-10 (std)	Top-100 (mean)	Top-100 (std)	Top-1000 (mean)	Top-1000 (std)
1	2685.7	0.9	2726.0	0.0	2740.0	0.0
2	2683.2	1.4	2725.3	0.45826	2740.0	0.0
3	2679.0	0.0	2725.0	0.0	2740.0	0.0
4	2662.9	0.7	2724.6	0.4899	2740.0	0.0
5	2657.0	0.0	2726.0	0.0	2740.0	0.0
6	2234.7	52.84515	2616.2	26.06837	2740.0	0.44721
7	1191.5	141.44981	2592.0	78.01538	2741.0	0.0
8	1069.0	147.85331	2536.7	76.17749	2741.0	0.0
9	1361.2	24.95115	2472.1	8.6539	2737.3	0.45826
10	943.1	207.5902	2486.7	178.39566	2741.0	0.0

(c)

Table 6.60: Top-10 results for Mazurkas to Experiment #4a.

6.7.3 Discussion: experiment #4a

Best results

Covers80 gets the best mean [MR](#) from the classification done by naive Bayes being trained with Covers1000 and using the Top-50 models. YouTubeCovers has the best result by the classification with naive Bayes also, train dataset as Covers1000, and the samples being produced with the Top-40 models. The best mean [MR](#) for Covers1000 is obtained with naive Bayes classification trained with SHS9K and using Top-50 models. Lastly, Mazurkas produce the best result with a naive Bayes model trained with SHS9K and with 40-dimensional samples. All best results are obtained using naive Bayes, so this suggests that this classifier has good potential for the task of this experiment.

Regarding the actual values of mean [MR](#) from the best results we have: 3.99186 for Mazurkas, 13.42257 for YouTubeCovers, 33.97812 for Covers80, and 146.5084 for Covers1000. The order is the same we had in Experiment #2, reflecting the intrinsic difficulty of retrieving versions from each dataset.

Comparative results

Figure 6.14: Summarized results to experiment #4a by dimension (a), and by classifier (b).

Analysing results beyond the Top-10, we can see in Figure 6.14a that the quality of the experiments do not grow up as the dimension gets higher. This is also observed in Experiment #3a, so our hypothesis that fusing similar information does not actually help in the context of these experiments gets confirmed.

Figure 6.14b shows us that naive Bayes is indeed the best performing classifier for this specific experiment. Random forest also has good average performance, and this was also observed in experiment #3a, so it is safe to consider it a robust classifier in the context of our datasets and our experiments.

6.7.4 Results: experiment #4b

While analysing the following results, be aware that the classification runs done with SHS9K as training dataset are still running to this date ($\approx 35\%$ is finished). So Tables 6.61 to 6.64 display the current partial results.

Covers80

line id	train dataset	length	models	classifier
1	covers1000	3	{chroma_stft, basic_stats_1, cosine_distance_oti}	ada_boost
2	mazurkas	3	{beat_synchronous_chroma_cens, basic_stats_2, manhattan_distance_oti}	ada_boost
3	mazurkas	3	{chroma_stft, basic_stats_1, cosine_distance_oti}	ada_boost
4	youtubecovers	3	{beat_synchronous_chroma_cens, basic_stats_2, manhattan_distance_oti}	naive_bayes
5	youtubecovers	3	{chroma_stft, diff_stats_1, cosine_distance_oti}	naive_bayes
6	covers1000	3	{beat_synchronous_chroma_cens, basic_stats_2, manhattan_distance_oti}	naive_bayes
7	covers1000	3	{chroma_cqt, vector_quantization_default, cosine_distance}	naive_bayes
8	covers1000	3	{chroma_stft, diff_stats_1, cosine_distance_oti}	naive_bayes
9	covers1000	3	{beat_synchronous_chroma_cens, basic_stats_2, manhattan_distance_oti}	naive_bayes
10	covers1000	3	{chroma_stft, diff_stats_1, cosine_distance_oti}	ada_boost

(a)

line id	MR (mean)	MR (std)	MRR (mean)	MRR (std)	MDR (mean)	MDR (std)	MAP (mean)	MAP (std)
1	33.33313	1.28237	0.2385	0.01361	19.4	1.57797	0.2385	0.01361
2	33.37063	0.53799	0.27669	0.00578	19.0	1.18322	0.27669	0.00578
3	33.37438	0.64621	0.27402	0.00556	17.7	1.07703	0.27402	0.00556
4	33.48	0.17184	0.26881	0.0041	13.75	0.40311	0.26881	0.0041
5	33.53375	0.12432	0.26831	0.00399	14.7	0.5099	0.26831	0.00399
6	33.655	0.11812	0.26308	0.00168	17.25	0.25	0.26308	0.00168
7	33.83375	0.0738	0.26111	0.00115	19.0	0.22361	0.26111	0.00115
8	33.97812	0.02728	0.27669	0.00206	15.0	0.3873	0.27669	0.00206
9	34.0225	0.09451	0.27478	0.00113	15.35	0.39051	0.27478	0.00113
10	34.11688	1.58241	0.22903	0.02695	18.6	2.36432	0.22903	0.02695

(b)

line id	Top-1 (mean)	Top-1 (std)	Top-10 (mean)	Top-10 (std)	Top-100 (mean)	Top-100 (std)	Top-1000 (mean)	Top-1000 (std)
1	24.1	2.62488	64.6	1.90788	147.8	2.4	160.0	0.0
2	31.9	0.7	65.7	1.9	147.2	0.9798	160.0	0.0
3	31.8	1.07703	65.3	1.34536	147.0	1.18322	160.0	0.0
4	31.3	0.9	66.3	1.48661	142.3	0.64031	160.0	0.0
5	31.0	0.89443	68.2	1.07703	142.6	0.66332	160.0	0.0
6	31.2	0.4	63.0	0.63246	148.1	0.3	160.0	0.0
7	31.2	0.4	62.5	0.92195	147.0	0.0	160.0	0.0
8	32.9	0.53852	68.6	0.4899	146.9	1.04403	160.0	0.0
9	32.3	0.45826	67.0	0.63246	145.8	0.6	160.0	0.0
10	22.2	5.34416	64.5	4.34166	145.5	2.33452	160.0	0.0

(c)

Table 6.61: Top-10 results for Covers80 to Experiment #4b.

YouTubeCovers

line id	train dataset	length	models	classifier
1	covers1000	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean} {beat_synchronous_chroma_cens, statistical_summarization_2, monte_carlo_distance}	logistic_regression
2	mazurkas	3	{pitch_contour_segmentation, markov_chain, circular_manhattan} {beat_synchronous_chroma_cens, basic_stats_2, manhattan_distance_oti} {pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	logistic_regression
3	covers1000	3	{pitch_contour_segmentation, markov_chain, circular_manhattan} {pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	logistic_regression
4	covers1000	3	{beat_synchronous_chroma_cens, statistical_summarization_2, monte_carlo_distance} {rms, diff_stats_1, cosine_distance}	logistic_regression
5	mazurkas	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean} {beat_synchronous_chroma_cens, statistical_summarization_2, monte_carlo_distance} {mfcc, statistical_summarization_2, monte_carlo_distance}	logistic_regression
6	covers1000	2	{chroma_cqt, vector_quantization_default, cosine_distance} {pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	logistic_regression
7	mazurkas	3	{pitch_contour_segmentation, markov_chain, circular_manhattan} {pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	logistic_regression
8	covers1000	3	{beat_synchronous_chroma_cens, statistical_summarization_2, monte_carlo_distance} {pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	logistic_regression
9	covers1000	3	{pitch_contour_segmentation, markov_chain, circular_manhattan} {pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	logistic_regression
10	mazurkas	3	{beat_synchronous_chroma_cens, statistical_summarization_2, monte_carlo_distance} {temporal_rhythm_histogram, bypass, cosine_distance} {chroma_stft, basic_stats_1, cosine_distance_oti}	logistic_regression
			{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	
			{pitch_contour_segmentation, markov_chain, circular_manhattan}	

(a)

line id	MR (mean)	MR (std)	MRR (mean)	MRR (std)	MDR (mean)	MDR (std)	MAP (mean)	MAP (std)
1	5.63714	0.05424	0.70923	0.00208	1.0	0.0	0.39507	0.00157
2	6.37714	0.01054	0.73284	0.00068	1.0	0.0	0.40336	0.00026
3	6.43486	0.06823	0.69203	0.00196	1.0	0.0	0.35837	0.00077
4	6.44857	0.0814	0.69852	0.00121	1.0	0.0	0.36465	0.00077
5	6.47743	0.00564	0.6997	0.00017	1.0	0.0	0.37871	0.00023
6	6.48914	0.06202	0.69808	0.00101	1.0	0.0	0.36424	0.00059
7	6.63886	0.01071	0.72393	0.00021	1.0	0.0	0.39434	0.00014
8	6.63914	0.06962	0.68407	0.00193	1.0	0.0	0.36068	0.00217
9	6.64743	0.01311	0.70585	0.00251	1.0	0.0	0.36096	0.0022
10	6.67971	0.0088	0.72049	0.00115	1.0	0.0	0.39148	0.00018

(b)

line id	Top-1 (mean)	Top-1 (std)	Top-10 (mean)	Top-10 (std)	Top-100 (mean)	Top-100 (std)	Top-1000 (mean)	Top-1000 (std)
1	221.9	1.04403	306.2	1.16619	348.9	0.3	350.0	0.0
2	232.3	0.45826	307.0	0.0	348.0	0.0	350.0	0.0
3	210.9	1.22066	298.4	1.0198	349.0	0.0	350.0	0.0
4	217.6	0.4899	299.8	0.74833	348.9	0.3	350.0	0.0
5	211.0	0.0	304.2	0.4	349.0	0.0	350.0	0.0
6	217.6	0.4899	299.5	0.67082	348.7	0.45826	350.0	0.0
7	230.0	0.0	305.0	0.0	348.0	0.0	350.0	0.0
8	209.4	1.2	296.9	0.83066	348.0	0.0	350.0	0.0
9	218.0	1.48324	303.9	0.3	346.6	0.4899	350.0	0.0
10	227.4	0.66332	300.0	0.0	349.0	0.0	350.0	0.0

(c)

Table 6.62: Top-10 results for YouTubeCovers to Experiment #4b.

Covers1000

line id	train dataset	length	models	classifier
1	mazurkas	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	logistic_regression
2	mazurkas	3	{tonnetz, diff_stats_1, manhattan_distance}	logistic_regression
3	mazurkas	3	{rhythm_histogram, bypass, cosine_distance}	logistic_regression
4	mazurkas	3	{chroma_stft, basic_stats_1, cosine_distance_oti}	logistic_regression
5	mazurkas	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	logistic_regression
6	mazurkas	3	{tonnetz, diff_stats_1, manhattan_distance}	logistic_regression
7	mazurkas	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	logistic_regression
8	mazurkas	3	{beat_synchronous_chroma_cens, statistical_summarization_2, monte_carlo_distance}	logistic_regression
9	mazurkas	3	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	logistic_regression
10	mazurkas	3	{tonnetz, diff_stats_1, manhattan_distance}	logistic_regression

(a)

line id	MR (mean)	MR (std)	MRR (mean)	MRR (std)	MDR (mean)	MDR (std)	MAP (mean)	MAP (std)
1	109.0794	0.23776	0.30175	0.00065	16.5	0.3873	0.23293	0.00034
2	110.2433	0.05417	0.29784	0.00022	17.0	0.0	0.23014	0.00019
3	110.2546	0.05547	0.29754	0.00048	17.0	0.0	0.22995	0.00031
4	110.4845	0.02306	0.30212	0.00015	17.0	0.0	0.23172	0.00022
5	111.1542	0.0444	0.3025	0.0002	18.1	0.2	0.23237	0.00023
6	111.9633	0.03316	0.29852	0.00021	18.0	0.0	0.23083	0.0002
7	112.0256	0.108	0.30206	0.00028	17.0	0.0	0.22708	0.00019
8	112.1167	0.13261	0.2939	0.00042	18.0	0.0	0.22709	0.00044
9	112.8789	0.19713	0.31051	0.0005	20.0	0.0	0.23483	0.00037
10	114.492	0.05107	0.29445	0.00057	19.75	0.25	0.22728	0.00034

(b)

line id	Top-1 (mean)	Top-1 (std)	Top-10 (mean)	Top-10 (std)	Top-100 (mean)	Top-100 (std)	Top-1000 (mean)	Top-1000 (std)
1	228.7	0.9	440.0	0.89443	707.0	0.0	1000.0	0.0
2	225.0	0.0	432.9	0.53852	700.9	0.3	1000.0	0.0
3	224.4	0.4899	433.4	0.4899	701.1	0.3	1000.0	0.0
4	233.8	0.4	442.9	1.57797	700.8	0.6	1000.0	0.0
5	232.6	0.4899	436.5	0.80623	708.8	1.46969	1000.0	0.0
6	223.9	0.3	436.5	0.80623	692.8	0.74833	1000.0	0.0
7	236.0	0.44721	437.1	0.3	697.0	0.0	1000.0	0.0
8	222.5	0.80623	425.8	0.6	698.4	0.66332	1000.0	0.0
9	253.4	0.66332	413.0	1.18322	715.2	0.74833	1000.0	0.0
10	226.7	1.00499	423.1	0.83066	698.4	0.66332	1000.0	0.0

(c)

Table 6.63: Top-10 results for Covers1000 to Experiment #4b.

Mazurkas

line id	train dataset	length	models	classifier
1	shs9k	2	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
2	shs9k	2	{zero_crossing_rate, basic_stats_1, chebyshev_distance}	random_forest
3	shs9k	2	{chroma_cqt, vector_quantization_default, cosine_distance}	random_forest
4	shs9k	2	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
5	shs9k	2	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
6	shs9k	2	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
7	shs9k	2	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
8	shs9k	2	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
9	shs9k	2	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest
10	shs9k	2	{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean}	random_forest

(a)

line id	MR (mean)	MR (std)	MRR (mean)	MRR (std)	MDR (mean)	MDR (std)	MAP (mean)	MAP (std)
1	1.97322	0.05831	0.93372	0.00406	1.0	0.0	0.62158	0.01322
2	1.9873	0.08763	0.94935	0.00224	1.0	0.0	0.7264	0.0059
3	2.00795	0.05173	0.94463	0.00199	1.0	0.0	0.62359	0.00578
4	2.03068	0.05444	0.94547	0.00261	1.0	0.0	0.62956	0.00884
5	2.05932	0.10032	0.93815	0.00291	1.0	0.0	0.57592	0.0083
6	2.0633	0.07103	0.93469	0.00446	1.0	0.0	0.5783	0.01642
7	2.0903	0.0641	0.93903	0.00249	1.0	0.0	0.58748	0.00799
8	2.09861	0.06603	0.93325	0.00291	1.0	0.0	0.66314	0.00584
9	2.12331	0.11285	0.95074	0.0023	1.0	0.0	0.73001	0.00662
10	2.13769	0.09337	0.93815	0.00565	1.0	0.0	0.59706	0.01346

(b)

line id	Top-1 (mean)	Top-1 (std)	Top-10 (mean)	Top-10 (std)	Top-100 (mean)	Top-100 (std)	Top-1000 (mean)	Top-1000 (std)
1	2457.3	21.89087	2697.8	3.73631	2734.5	1.62788	2741.0	0.0
2	2526.4	9.40425	2700.7	4.42832	2732.2	1.32665	2741.0	0.0
3	2507.0	10.30534	2699.5	2.06155	2734.5	1.36015	2741.0	0.0
4	2515.5	11.47388	2696.5	4.00625	2733.3	1.79165	2741.0	0.0
5	2474.9	12.87206	2700.3	3.13209	2732.8	1.46969	2741.0	0.0
6	2458.6	21.22828	2701.6	3.90384	2732.9	1.22066	2741.0	0.0
7	2483.1	9.67936	2698.2	3.84187	2732.7	1.48661	2741.0	0.0
8	2451.2	11.83047	2699.3	2.05183	2732.9	1.81384	2741.0	0.0
9	2537.5	11.1018	2697.7	3.0348	2731.2	2.44131	2741.0	0.0
10	2482.0	26.95923	2697.4	4.22374	2732.8	1.46969	2741.0	0.0

(c)

Table 6.64: *Top-10 results for Mazurkas to Experiment #4b.***6.7.5 Discussion: experiment #4b****Best results**

The best results for experiment #4b are: Covers80 by ada boost trained with Covers1000 and 3-dimensional samples; YouTubeCovers by logistic regression with Covers1000 as train dataset and using 3 models to obtain the samples; Covers1000 by logistic regression, trained with Mazurkas and 3-D samples; Mazurkas by random forest trained with SHS9K and 2-dimensional samples.

Both Covers80 and YouTubeCovers have the three models that lead to the best CSI results with tonal features, while Covers1000 have Pitch Contour Segmentation, Tonnetz, and Rhythm Histogram which is a rhythmic feature. In Experiment #3b, Covers1000 also needed a rhythmic feature to achieve the best results, and this can be an indication that versions in Covers1000 can be better retrieved with the aid of rhythmic similarity models. The order of the datasets is the same: Mazurkas (with 1.97322 mean MR), YouTubeCovers (5.63714), Covers80 (33.33313), and Covers1000 (109.0794).

Comparative results

Figure 6.15: Summarized results to experiment #4a by dimension (a), and by classifier (b).

Investigating the overall results, Figure 6.15a summarizes the MR values by the dimension of the samples. As observed in experiment #3b, the filtered models lead to better results as the dimension grows. Figure 6.15b displays the values of MR by classifier. All classifiers, excluding decision tree, have their average MR quite close to each other, with a slightly better mean for logistic regression, which shows up in all Top-10 results for YouTubeCovers and Covers1000.

dataset	best MR (experiment #2)	best mean MR (experiment #4a)	best mean MR (experiment #4b)
Covers80	41.575	33.97812	33.33313
YouTubeCovers	7.97143	13.42257	5.63714
Covers1000	144.041	146.5084	109.0794
Mazurkas	4.15724	3.99186	1.97322

Table 6.65: Best results from Experiments #4 compared with Experiment #2.

Finally, we can compare results from both experiments presented in this Section with the results from the main CSI experiment. Table 6.65 shows that, in experiment #4a, Covers80 and Mazurkas already have better results compared to experiment #2. Experiment #4b leads to all datasets having better results than the original CSI experiment. This is a strong result in favor of the use of CSC methods for the CSI problem.

6.8 Experiment #5: Dataset modifications

6.8.1 Experiment design

In this experiment we apply all dataset modifications presented in Section 5.4, and then we compute all CSI metrics presented in Section 3.1.4. The main goal of Experiment #5 is to verify if any modification leads to better CSI results when compared to the metrics obtained with the original datasets.

In the following Section the best results are displayed for every one of the 5 CSI datasets. All results are published in https://rppbodo.github.io/phd/experiment_5.html.

6.8.2 Results

Covers80

dataset	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
covers80	41.575	0.19359	31.0	0.19359	21.0	46.0	142.0	160.0
covers80_30_beg	52.00625	0.13789	37.5	0.13789	13.0	42.0	128.0	160.0
covers80_30_end	53.9	0.13827	45.0	0.13827	14.0	35.0	131.0	160.0
covers80_30_mid	46.19375	0.17388	28.0	0.17388	18.0	50.0	134.0	160.0
covers80_bartsch_wakefield	52.4875	0.11902	44.0	0.11902	9.0	35.0	134.0	160.0
covers80_bass	42.125	0.20927	24.0	0.20927	22.0	57.0	135.0	160.0
covers80_cooper_foote	51.025	0.14076	40.0	0.14076	11.0	42.0	136.0	160.0
covers80_drums	54.3375	0.07624	43.0	0.07624	3.0	30.0	129.0	160.0
covers80_other	46.33125	0.15671	34.5	0.15671	12.0	54.0	134.0	160.0
covers80_qm-segmenter	51.55	0.1138	36.5	0.1138	6.0	43.0	126.0	160.0
covers80_rms_10	61.7875	0.07634	49.5	0.07634	5.0	24.0	120.0	160.0
covers80_rms_20	52.4	0.08832	40.0	0.08832	6.0	24.0	130.0	160.0
covers80_rms_30	50.0625	0.13294	39.0	0.13294	14.0	33.0	136.0	160.0
covers80_rms_40	48.6125	0.14707	37.5	0.14707	15.0	41.0	135.0	160.0
covers80_rms_50	47.11875	0.15756	36.0	0.15756	15.0	43.0	137.0	160.0
covers80_rms_60	43.5125	0.18049	28.0	0.18049	17.0	51.0	134.0	160.0
covers80_rms_70	43.95625	0.17219	29.0	0.17219	15.0	52.0	137.0	160.0
covers80_rms_80	42.975	0.18578	28.0	0.18578	19.0	52.0	142.0	160.0
covers80_rms_90	42.06875	0.20586	26.5	0.20586	20.0	56.0	141.0	160.0
covers80_segmentino	58.0625	0.08312	49.5	0.08312	5.0	28.0	123.0	160.0
covers80_siplca	53.46875	0.10518	45.5	0.10518	8.0	31.0	131.0	160.0
covers80_vocals	51.19375	0.21095	34.5	0.21095	23.0	52.0	127.0	160.0
covers80_vocals_rms_10	49.34375	0.18072	37.0	0.18072	19.0	46.0	134.0	160.0
covers80_vocals_rms_20	47.65	0.14985	33.5	0.14985	12.0	48.0	134.0	160.0
covers80_vocals_rms_30	44.35625	0.19798	35.5	0.19798	21.0	51.0	141.0	160.0
covers80_vocals_rms_40	42.64375	0.16433	31.0	0.16433	15.0	48.0	140.0	160.0
covers80_vocals_rms_50	42.38125	0.16205	32.0	0.16205	16.0	43.0	141.0	160.0
covers80_vocals_rms_60	42.3375	0.16502	28.5	0.16502	16.0	48.0	140.0	160.0
covers80_vocals_rms_70	41.3	0.20834	22.5	0.20834	20.0	61.0	134.0	160.0
covers80_vocals_rms_80	41.975	0.17761	28.5	0.17761	18.0	45.0	144.0	160.0
covers80_vocals_rms_90	41.75	0.18389	31.0	0.18389	20.0	47.0	141.0	160.0

Table 6.66: The best results for each modified dataset for Covers80.

YouTubeCovers

dataset	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
youtubecovers	7.97143	0.6942	1.0	0.36114	219.0	296.0	345.0	350.0
youtubecovers_30_beg	20.96571	0.34045	9.0	0.1322	88.0	186.0	341.0	350.0
youtubecovers_30_end	27.49143	0.24078	13.0	0.0861	48.0	152.0	328.0	350.0
youtubecovers_30_mid	22.80286	0.29309	9.0	0.11305	61.0	193.0	335.0	350.0
youtubecovers_bartsch_wakefield	19.92571	0.38321	5.0	0.13723	95.0	213.0	337.0	350.0
youtubecovers_bass	16.37143	0.5491	2.0	0.27495	166.0	241.0	340.0	350.0
youtubecovers_cooper_foote	28.00857	0.22246	14.0	0.08266	41.0	152.0	332.0	350.0
youtubecovers_drums	37.15429	0.14012	23.0	0.05417	21.0	114.0	320.0	350.0
youtubecovers_other	14.06	0.47627	3.0	0.23085	131.0	240.0	343.0	350.0
youtubecovers_qm-segmenter	27.48	0.22917	13.0	0.08615	44.0	160.0	331.0	350.0
youtubecovers_rms_10	37.76286	0.13124	22.0	0.05137	20.0	105.0	322.0	350.0
youtubecovers_rms_20	27.07143	0.25139	12.5	0.09752	53.0	165.0	334.0	350.0
youtubecovers_rms_30	16.70857	0.39305	5.0	0.16382	97.0	229.0	340.0	350.0
youtubecovers_rms_40	14.53429	0.48738	3.0	0.21466	137.0	243.0	342.0	350.0
youtubecovers_rms_50	11.89714	0.54654	2.0	0.25512	158.0	266.0	342.0	350.0
youtubecovers_rms_60	11.44286	0.59266	2.0	0.28625	174.0	275.0	338.0	350.0
youtubecovers_rms_70	9.13429	0.62006	1.0	0.32162	184.0	286.0	344.0	350.0
youtubecovers_rms_80	8.18857	0.66438	1.0	0.34196	202.0	300.0	346.0	350.0
youtubecovers_rms_90	8.77143	0.67878	1.0	0.35952	211.0	296.0	346.0	350.0
youtubecovers_segmentino	28.6	0.23981	16.5	0.08817	52.0	145.0	329.0	350.0
youtubecovers_siplca	22.59429	0.32043	8.0	0.12486	73.0	192.0	335.0	350.0
youtubecovers_vocals	12.77143	0.6162	1.0	0.35571	192.0	261.0	339.0	350.0
youtubecovers_vocals_rms_10	18.93714	0.32488	7.0	0.127	70.0	204.0	341.0	350.0
youtubecovers_vocals_rms_20	10.34	0.55453	2.0	0.25723	157.0	264.0	347.0	350.0
youtubecovers_vocals_rms_30	10.81429	0.64884	1.0	0.3301	198.0	287.0	342.0	350.0
youtubecovers_vocals_rms_40	8.42571	0.68883	1.0	0.36878	216.0	287.0	347.0	350.0
youtubecovers_vocals_rms_50	9.80286	0.67666	1.0	0.37006	207.0	292.0	343.0	350.0
youtubecovers_vocals_rms_60	9.19143	0.67039	1.0	0.37298	205.0	291.0	343.0	350.0
youtubecovers_vocals_rms_70	8.42857	0.67708	1.0	0.37043	212.0	293.0	344.0	350.0
youtubecovers_vocals_rms_80	9.01714	0.68146	1.0	0.36879	213.0	293.0	343.0	350.0
youtubecovers_vocals_rms_90	9.17143	0.66096	1.0	0.35772	201.0	289.0	342.0	350.0

Table 6.67: The best results for each modified dataset for YouTubeCovers.

Covers1000

dataset	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
covers1000	144.041	0.25731	35.0	0.19159	201.0	366.0	636.0	1000.0
covers1000_30_beg	213.562	0.12522	106.0	0.08702	81.0	200.0	490.0	1000.0
covers1000_30_end	205.748	0.08836	117.5	0.06245	45.0	172.0	469.0	1000.0
covers1000_30_mid	206.592	0.08778	109.5	0.0622	42.0	161.0	485.0	1000.0
covers1000_bartsch_wakefield	225.575	0.09385	115.5	0.06538	50.0	165.0	480.0	1000.0
covers1000_bass	150.027	0.32957	27.0	0.26457	280.0	421.0	649.0	1000.0
covers1000_cooper_foote	212.222	0.07075	126.0	0.05355	35.0	125.0	457.0	1000.0
covers1000_drums	246.203	0.1013	119.0	0.07178	54.0	178.0	468.0	1000.0
covers1000_other	164.52	0.139	67.0	0.1007	86.0	237.0	582.0	1000.0
covers1000_qm-segmenter	214.766	0.08124	118.5	0.05836	43.0	141.0	459.0	1000.0
covers1000_rms_10	264.19	0.02966	184.5	0.02228	7.0	60.0	343.0	1000.0
covers1000_rms_20	242.019	0.04186	149.5	0.02992	14.0	79.0	392.0	1000.0
covers1000_rms_30	226.976	0.06397	135.0	0.04325	30.0	125.0	428.0	1000.0
covers1000_rms_40	212.291	0.14401	99.5	0.10373	102.0	214.0	503.0	1000.0
covers1000_rms_50	192.557	0.18258	78.0	0.135	139.0	263.0	527.0	1000.0
covers1000_rms_60	163.671	0.20892	61.0	0.15403	160.0	301.0	592.0	1000.0
covers1000_rms_70	156.124	0.22716	52.5	0.16557	176.0	331.0	612.0	1000.0
covers1000_rms_80	149.235	0.24245	39.5	0.17682	186.0	352.0	629.0	1000.0
covers1000_rms_90	139.806	0.27382	30.0	0.20739	218.0	381.0	662.0	1000.0
covers1000_segmentino	218.62	0.07973	126.0	0.05763	39.0	152.0	458.0	1000.0
covers1000_siplca	186.598	0.07564	99.0	0.05182	33.0	152.0	503.0	1000.0
covers1000_vocals	156.711	0.31149	32.0	0.24498	264.0	404.0	638.0	1000.0
covers1000_vocals_rms_10	227.618	0.06649	141.5	0.0465	35.0	115.0	424.0	1000.0
covers1000_vocals_rms_20	174.339	0.15585	72.0	0.1097	107.0	239.0	558.0	1000.0
covers1000_vocals_rms_30	155.591	0.2271	46.0	0.16291	169.0	336.0	616.0	1000.0
covers1000_vocals_rms_40	141.942	0.25919	35.0	0.18761	200.0	369.0	648.0	1000.0
covers1000_vocals_rms_50	154.75	0.25097	37.0	0.18189	190.0	369.0	635.0	1000.0
covers1000_vocals_rms_60	152.472	0.26559	37.0	0.19624	213.0	381.0	633.0	1000.0
covers1000_vocals_rms_70	150.976	0.2475	38.0	0.18228	192.0	358.0	635.0	1000.0
covers1000_vocals_rms_80	151.975	0.2476	39.5	0.18165	195.0	336.0	639.0	1000.0
covers1000_vocals_rms_90	142.65	0.26677	40.0	0.19668	212.0	366.0	654.0	1000.0

Table 6.68: The best results for each modified dataset for Covers1000.

Mazurkas

Mazurkas is a dataset whose tracks are mainly piano recordings, so it is not possible to explore some dataset modification techniques: the 4 source separation datasets can not be created; the 9 secondary datasets build using frame selection by vocals' RMS also can not be created. Thus we have only 17 modified datasets to experiment.

dataset	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
mazurkas	4.15724	0.95774	1.0	0.82286	2561.0	2714.0	2728.0	2739.0
mazurkas_30_beg	2.81284	0.92509	1.0	0.55828	2434.0	2690.0	2727.0	2740.0
mazurkas_30_end	4.33382	0.87207	1.0	0.36153	2239.0	2633.0	2722.0	2741.0
mazurkas_30_mid	3.12733	0.88732	1.0	0.41965	2294.0	2645.0	2728.0	2741.0
mazurkas_bartsch_wakefield	3.80409	0.88995	1.0	0.38092	2308.0	2648.0	2720.0	2741.0
mazurkas_cooper_foote	4.72273	0.82289	1.0	0.31283	2062.0	2614.0	2720.0	2741.0
mazurkas_qm-segmenter	5.94856	0.76276	1.0	0.22742	1832.0	2545.0	2713.0	2740.0
mazurkas_rms_10	6.76323	0.8015	1.0	0.36347	1978.0	2581.0	2718.0	2738.0
mazurkas_rms_20	5.72492	0.73234	1.0	0.22176	1719.0	2538.0	2719.0	2740.0
mazurkas_rms_30	4.62532	0.85361	1.0	0.38133	2182.0	2629.0	2727.0	2739.0
mazurkas_rms_40	3.94892	0.91145	1.0	0.52903	2385.0	2687.0	2727.0	2739.0
mazurkas_rms_50	3.89821	0.92668	1.0	0.52952	2448.0	2691.0	2725.0	2739.0
mazurkas_rms_60	3.55308	0.94471	1.0	0.63254	2512.0	2701.0	2729.0	2739.0
mazurkas_rms_70	3.52426	0.95366	1.0	0.71281	2543.0	2711.0	2730.0	2739.0
mazurkas_rms_80	3.99964	0.90595	1.0	0.46992	2363.0	2671.0	2725.0	2740.0
mazurkas_rms_90	3.95841	0.92943	1.0	0.60055	2467.0	2676.0	2722.0	2741.0
mazurkas_segmentino	4.77599	0.83857	1.0	0.23812	2136.0	2584.0	2721.0	2741.0
mazurkas_siplca	5.97337	0.81504	1.0	0.25614	2042.0	2548.0	2712.0	2741.0

Table 6.69: The best results for each modified dataset for Mazurkas.

SHS9K

The experiments with SHS9K modified datasets are still running to the date of this publication, so the following table shows the partial best results.

dataset	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
shs9k	47.57883	0.40387	6.0	0.05102	3008.0	5188.0	8067.0	9265.0
shs9k_30_beg	83.35225	0.17503	34.0	0.01713	1013.0	2767.0	6859.0	9275.0
shs9k_30_mid	45.83082	0.2384	13.0	0.03149	1282.0	4161.0	8272.0	9267.0
shs9k_30_end	87.48568	0.14304	33.0	0.01848	661.0	2619.0	7028.0	9235.0
shs9k_bartsch_wakefield	81.08249	0.16252	29.0	0.01845	819.0	2868.0	7210.0	9257.0
shs9k_bass	59.93216	0.36286	10.0	0.0621	2729.0	4644.0	7685.0	9253.0
shs9k_cooper_foote	90.88768	0.13307	36.0	0.01722	620.0	2413.0	6968.0	9233.0
shs9k_drums	127.94648	0.0541	77.0	0.00954	163.0	979.0	5441.0	9253.0
shs9k_other	63.8459	0.22859	16.0	0.02854	1268.0	3892.0	7779.0	9242.0
shs9k_qm-segmenter	81.95057	0.16444	28.0	0.02021	807.0	2910.0	7196.0	9242.0
shs9k_rms_10	109.81047	0.08204	57.0	0.0112	324.0	1475.0	6119.0	9249.0
shs9k_rms_20	91.6583	0.14435	40.0	0.01622	757.0	2440.0	6643.0	9273.0
shs9k_rms_30	74.96059	0.22647	24.0	0.02432	1425.0	3404.0	7236.0	9266.0
shs9k_rms_40	62.03565	0.29329	15.0	0.03327	2004.0	4102.0	7545.0	9274.0
shs9k_rms_50	55.80713	0.34819	11.0	0.04142	2504.0	4640.0	7768.0	9270.0
shs9k_rms_60	50.94012	0.37985	8.0	0.04729	2775.0	4980.0	7929.0	9268.0
shs9k_rms_70	48.25942	0.40286	7.0	0.05088	3037.0	5144.0	8000.0	9274.0
shs9k_rms_80	46.27256	0.41185	6.0	0.05264	3096.0	5274.0	8050.0	9275.0
shs9k_rms_90	46.07915	0.41066	6.0	0.05257	3080.0	5267.0	8076.0	9271.0
shs9k_segmentino	77.40965	0.18467	25.0	0.02181	957.0	3201.0	7355.0	9236.0
shs9k_siplca	81.09412	0.14743	31.0	0.01787	689.0	2724.0	7154.0	9255.0
shs9k_vocals	49.71732	0.48504	3.0	0.09081	3956.0	5498.0	7940.0	9273.0
shs9k_vocals_rms_10	90.95994	0.12264	36.0	0.01608	505.0	2340.0	6888.0	9250.0
shs9k_vocals_rms_20	68.31585	0.25591	18.0	0.03019	1629.0	3834.0	7409.0	9266.0
shs9k_vocals_rms_30	56.14236	0.37507	8.0	0.05122	2754.0	4861.0	7809.0	9266.0
shs9k_vocals_rms_40	49.30336	0.43569	5.0	0.06648	3341.0	5409.0	7999.0	9275.0
shs9k_vocals_rms_50	45.41536	0.4578	4.0	0.07188	3571.0	5551.0	8085.0	9270.0
shs9k_vocals_rms_60	43.63246	0.4593	4.0	0.0693	3575.0	5602.0	8148.0	9276.0
shs9k_vocals_rms_70	43.42462	0.44726	4.0	0.06443	3420.0	5550.0	8126.0	9270.0
shs9k_vocals_rms_80	43.30401	0.43289	5.0	0.05862	3289.0	5433.0	8182.0	9278.0
shs9k_vocals_rms_90	44.47351	0.41457	6.0	0.0536	3089.0	5354.0	8107.0	9275.0

Table 6.70: The best results for each modified dataset for SHS9K.

6.8.3 Discussion

Best results

The analysis of the best results corresponds to looking for modified datasets that have better mean ranks than the original ones. Covers80 has one modified dataset (*vocals_rms_70*) with better mean rank; YouTubeCovers has none; Covers1000 has three (*rms_90*, *vocals_rms_90*, *vocals_rms_40*); Mazurkas has nine (*rms_40*, *rms_50*, *rms_60*, *rms_70*, *rms_80*, *rms_90*, *30_beg*, *30_mid*, *bartsch_wakefield*); and SHS9K has eight (*30_mid*, *rms_80*, *rms_90*, *vocals_rms_50*, *vocals_rms_60*, *vocals_rms_70*, *vocals_rms_80*, *vocals_rms_90*).

Clearly, datasets modified by frame selection appear more often (17 of the 21 that lead to better results), than the other types of modification techniques, followed by 4 datasets modified by segment selection. Analysing only the **MR**, none of the source separation modified datasets appeared.

While **MR** takes account of the ranks of the first versions in the retrieved lists, **MAP** uses the ranks from all versions (as explained in Section 3.1.4), so we also look for better results obtained by **MAP**. Covers80 has five datasets (*bass*, *rms_90*, *vocals*, *vocals_rms_30*, *vocals_rms_70*) with better mean rank; YouTubeCovers has also five (*vocals_rms_40*, *vocals_rms_50*, *vocals_rms_60*, *vocals_rms_70*, *vocals_rms_80*); Covers1000 has five likewise (*bass*, *rms_90*, *vocals*, *vocals_rms_60*, *vocals_rms_90*); Mazurkas has none; and SHS9K has eleven (*bass*, *rms_80*, *rms_90*, *vocals*, *vocals_rms_30*, *vocals_rms_40*, *vocals_rms_50*, *vocals_rms_60*, *vocals_rms_70*, *vocals_rms_80*, *vocals_rms_90*).

Again, the datasets modified by frame selection emerge more frequently (20 out of 26 techniques that produce higher **MAP** values), than the other types of dataset modifications. The other two types of modifications - segment selection and source separation - now switch places. All the remaining 6 modifications use source separation, and none better result is obtained using segment selection, when analysing the **MAP** metric.

Comparative results

Figure 6.16: Comparison of best results obtained with source separation secondary datasets.

Figure 6.16 shows us the best mean ranks obtained for 4 cover song datasets (please remember that it is not possible to extract sources from Mazurkas dataset). In this figure, the best mean rank for each dataset is highlighted with an ‘x’. Two datasets – Covers80 and Covers1000 – have their best results via source separation by the bass secondary datasets. The other two datasets – YouTubeCovers and SHS9K – have their best results with the isolated vocals datasets. Both sources hold mainly tonal information, which confirm the statements in the literature about this being the best music characteristic for CSI problem [SGH10, SSG12, CLX17].

Figure 6.17: Comparison of best results obtained with segment selection secondary datasets.

Comparing the best results obtained with segment selection, Figure 6.17 shows that YouTube-Covers has the best result with a thumbnailing technique (Bartsch and Wakefield), Covers1000 has the best result with a segmentation technique (SIPLCA), and three remaining datasets have their best results with the selection of arbitrary segments (Covers80 and SHS9K with the middle 30-second segments, and Mazurkas with the initial 30-second segments).

Figure 6.18: Comparison of best results obtained with frame selection secondary datasets.

Finally, Figure 6.18 shows us the best results for datasets obtained with frame selection methods. Firstly, we can check that the best mean rank values do not monotonically decrease with the increase of the percentage of retained frames. Secondly, the best results are not always obtained with the maximum percentage. There are two best results with 80% (*shs9k_vocals_rms* and *youtubecovers_rms*), two with 70% (*mazurkas_rms* and *covers80_vocals_rms*), and also two with 40% (*youtubecovers_vocals_rms* and *covers1000_vocals_rms*).

Lastly, it is possible to compare the frame selection process made with the songs' RMS values and with the vocals' RMS values (except with Mazurkas whose tracks do not have vocals). From 36 results (4 datasets $\times$ 9 percentage values) comparing relative pairs (same dataset with same percentage value), 32 values ($\approx 88\%$) are better with the vocals' RMS. This is a good discovery in favor of the frame selection technique we propose.

6.9 Experiment #6: Fusions

6.9.1 Experiment design

The main goal of this experiment is to try different fusion functions with similarity matrices obtained from the source separation modified datasets. From experiments #3 and #4 it is doubly verified that fusing filtered models leads to better results compared to Top-N models. So we fuse only the filtered models from the derivative dataset of each individual source.

We experiment with 4 alternative matrix fusion functions: 3 simple ones – minimum, maximum, and mean – and a more complex one, as presented in Section 5.5, *Similarity Network Fusion (SNF)*. Therefore we have here 4 modified datasets, 16 models, and 4 functions, leading to 262,144 ($16^4 \times 4$) fusion schemes. It should be remembered that Mazurkas recordings do not have the sources identified and separated by Open-Unmix [SULM19], so this dataset is not used in this experiment.

Tables 6.71 to 6.86 show the Top-5 results for each individual source dataset, each fusion function, and which models are fused to obtain the results. Please, refer to Appendix C to identify

which models are listed below, since they are displayed by their line identifiers. Also, all results are published in https://rppbodo.github.io/phd/experiment_6.html.

6.9.2 Results

Covers80

bass	model's drums	line id vocals	other	MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
6	2	6	13	27.675	0.36057	9.5	0.36057	47.0	81.0	149.0	160.0
6	9	6	10	27.675	0.36057	9.5	0.36057	47.0	81.0	149.0	160.0
6	5	6	5	27.675	0.36057	9.5	0.36057	47.0	81.0	149.0	160.0
6	13	6	2	27.675	0.36057	9.5	0.36057	47.0	81.0	149.0	160.0
6	10	6	9	27.675	0.36057	9.5	0.36057	47.0	81.0	149.0	160.0

Table 6.71: *Top-5 results for Covers80 fusing models using the minimum function.*

bass	model's drums	line id vocals	other	MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
6	12	14	12	28.0	0.32869	13.5	0.32869	41.0	77.0	150.0	160.0
6	12	14	4	28.0125	0.32711	13.5	0.32711	41.0	77.0	150.0	160.0
6	12	14	8	28.01875	0.32711	13.5	0.32711	41.0	77.0	150.0	160.0
6	12	14	0	28.01875	0.32711	13.5	0.32711	41.0	77.0	150.0	160.0
6	12	14	11	28.01875	0.32711	13.5	0.32711	41.0	77.0	150.0	160.0

Table 6.72: *Top-5 results for Covers80 fusing models using the maximum function.*

bass	model's drums	line id vocals	other	MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
6	0	6	11	23.73125	0.41531	10.0	0.41531	57.0	83.0	152.0	160.0
6	1	6	11	23.84375	0.41438	9.5	0.41438	57.0	83.0	152.0	160.0
6	0	6	0	24.5125	0.4273	9.0	0.4273	59.0	83.0	150.0	160.0
6	0	6	1	24.54375	0.42729	9.0	0.42729	59.0	84.0	150.0	160.0
6	1	6	0	24.5625	0.42689	9.0	0.42689	59.0	83.0	150.0	160.0

Table 6.73: *Top-5 results for Covers80 fusing models using the mean function.*

bass	model's drums	line id vocals	other	MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
3	8	11	5	44.08125	0.13177	29.5	0.13177	9.0	42.0	142.0	
3	8	11	3	44.275	0.11449	29.0	0.11449	7.0	46.0	140.0	
2	8	8	5	44.91875	0.1084	26.0	0.1084	7.0	41.0	137.0	
3	8	4	5	45.025	0.14034	30.0	0.14034	11.0	44.0	141.0	
3	8	8	5	45.2625	0.12966	31.0	0.12966	9.0	43.0	137.0	

Table 6.74: *Top-5 results for Covers80 fusing models using SNF.*

YouTubeCovers

bass	model's drums	line id vocals	other	MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
1	10	0	0	9.04857	0.56417	2.0	0.31359	163.0	272.0	347.0	
8	8	0	0	9.04857	0.56417	2.0	0.31359	163.0	272.0	347.0	
12	8	0	0	9.04857	0.56417	2.0	0.31359	163.0	272.0	347.0	
1	8	0	0	9.04857	0.56417	2.0	0.31359	163.0	272.0	347.0	
1	12	0	0	9.04857	0.56417	2.0	0.31359	163.0	272.0	347.0	

Table 6.75: *Top-5 results for YouTubeCovers fusing models using minimum function.*

bass	model's drums	line id vocals	other	MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
2	6	0	6	11.82571	0.61532	1.0	0.32795	190.0	261.0	340.0	
2	6	0	2	11.82571	0.61544	1.0	0.32507	190.0	260.0	340.0	
2	6	0	9	11.86571	0.61523	1.0	0.32741	190.0	260.0	341.0	
2	6	0	4	11.87143	0.61514	1.0	0.32739	190.0	260.0	340.0	
2	6	0	5	11.87143	0.61514	1.0	0.32739	190.0	260.0	340.0	

Table 6.76: *Top-5 results for YouTubeCovers fusing models using maximum function.*

bass	model's line id			MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
	drums	vocals	other								
0	4	0	2	7.63429	0.64876	1.0	0.33159	196.0	286.0	346.0	
0	3	0	2	7.74857	0.64938	1.0	0.33093	195.0	288.0	346.0	
4	3	0	0	8.00286	0.64513	1.0	0.35413	194.0	297.0	347.0	350.0
4	4	0	0	8.1	0.64107	1.0	0.35168	192.0	291.0	347.0	350.0
0	4	0	0	8.11429	0.69677	1.0	0.38713	218.0	294.0	344.0	350.0

Table 6.77: Top-5 results for YouTubeCovers fusing models using mean function.

bass	model's line id			MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
	drums	vocals	other								
7	0	8	9	22.30857	0.28747	8.0	0.12021	57.0	198.0	335.0	
4	0	8	9	22.51429	0.29568	11.0	0.12344	66.0	174.0	336.0	
9	5	5	0	22.60571	0.25172	9.0	0.11368	42.0	186.0	333.0	
8	5	8	0	22.83714	0.30203	10.0	0.14037	67.0	177.0	337.0	
9	5	8	0	22.85714	0.27738	10.0	0.12357	59.0	179.0	338.0	

Table 6.78: Top-5 results for YouTubeCovers fusing models using SNF.

Covers1000

bass	model's line id			MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
	drums	vocals	other								
0	11	0	0	97.947	0.34529	18.5	0.28203	293.0	439.0	739.0	
0	11	0	7	103.246	0.38502	12.0	0.3162	332.0	483.0	738.0	
0	8	0	5	103.246	0.38502	12.0	0.3162	332.0	483.0	738.0	
0	8	0	14	103.246	0.38502	12.0	0.3162	332.0	483.0	738.0	
0	8	0	8	103.246	0.38502	12.0	0.3162	332.0	483.0	738.0	

Table 6.79: Top-5 results for Covers1000 fusing models using minimum function.

bass	model's line id			MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
	drums	vocals	other								
0	1	15	6	149.799	0.33058	27.0	0.26457	281.0	425.0	649.0	
0	4	1	6	149.799	0.33058	27.0	0.26457	281.0	425.0	649.0	
0	1	3	6	149.799	0.33058	27.0	0.26457	281.0	425.0	649.0	
0	4	6	6	149.831	0.33118	28.0	0.26525	282.0	424.0	649.0	
0	1	6	6	149.831	0.33118	28.0	0.26525	282.0	424.0	649.0	

Table 6.80: Top-5 results for Covers1000 fusing models using maximum function.

bass	model's line id			MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
	drums	vocals	other								
0	1	0	3	93.464	0.43794	7.0	0.35771	385.0	537.0	779.0	
0	1	0	1	94.771	0.43178	8.0	0.35226	375.0	525.0	772.0	
0	0	0	0	98.65	0.36548	12.0	0.29382	301.0	483.0	750.0	
0	0	0	1	102.164	0.38365	11.0	0.30681	320.0	499.0	742.0	
0	15	0	0	102.758	0.38889	11.0	0.31825	331.0	496.0	760.0	

Table 6.81: Top-5 results for Covers1000 fusing models using mean function.

bass	model's line id			MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
	drums	vocals	other								
8	3	3	6	153.648	0.12984	65.0	0.09162	72.0	230.0	594.0	
0	3	3	6	154.185	0.139	66.0	0.10154	82.0	239.0	588.0	
0	3	3	5	161.74	0.11418	65.5	0.08688	57.0	220.0	583.0	
3	3	3	6	162.273	0.13289	67.0	0.09446	78.0	227.0	579.0	
0	11	3	6	163.958	0.11783	79.0	0.08224	67.0	205.0	551.0	

Table 6.82: Top-5 results for Covers1000 fusing models using SNF.

SHS9K

bass	model's line id			MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
	drums	vocals	other								
0	1	0	6	41.97728	0.31233	10.0	0.06505	1992.0	4738.0	8197.0	
0	13	0	2	67.60414	0.20474	19.0	0.02875	1066.0	3629.0	7705.0	
4	5	13	2	67.60575	0.20463	19.0	0.02875	1064.0	3629.0	7704.0	
5	3	3	5	69.6596	0.17229	27.0	0.01985	910.0	2964.0	7285.0	
13	4	9	5	73.58421	0.22815	20.0	0.02439	1335.0	3670.0	7423.0	

Table 6.83: Top-5 results for SHS9K fusing models using minimum function.

bass	model's line id			MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
	drums	vocals	other								
0	0	0	8	51.90308	0.33782	10.0	0.03659	2353.0	4737.0	7920.0	
0	0	0	7	52.00118	0.33741	10.0	0.03655	2350.0	4738.0	7916.0	
15	11	0	1	67.25867	0.19913	19.0	0.02638	1003.0	3595.0	7675.0	
5	14	11	1	71.31262	0.19336	22.0	0.0241	1018.0	3348.0	7561.0	
0	1	2	3	73.36496	0.16625	25.0	0.01841	798.0	3041.0	7397.0	

Table 6.84: *Top-5 results for SHS9K fusing models using maximum function.*

bass	model's line id			MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
	drums	vocals	other								
0	0	0	8	38.61393	0.46388	4.0	0.06979	3581.0	5727.0	8291.0	
0	0	0	7	38.86377	0.39672	6.0	0.05259	2811.0	5422.0	8319.0	
5	14	11	1	60.45348	0.21987	18.0	0.02653	1203.0	3763.0	7796.0	
15	11	0	1	60.92796	0.20144	18.0	0.02459	1037.0	3586.0	7796.0	
0	1	2	3	64.36528	0.18218	21.0	0.0207	886.0	3343.0	7656.0	

Table 6.85: *Top-5 results for SHS9K fusing models using mean function.*

bass	model's line id			MR	MRR	MDR	MAP	Top-1	Top-10	Top-100	Top-1000
	drums	vocals	other								
5	3	3	5	93.12061	0.10387	45.0	0.01248	412.0	1973.0	6639.0	
8	0	2	5	93.17779	0.09779	45.0	0.01238	370.0	1876.0	6592.0	
0	1	0	6	96.06612	0.12136	41.0	0.01424	526.0	2267.0	6683.0	
0	13	0	2	96.87982	0.08756	41.0	0.0136	278.0	1822.0	6786.0	
8	2	13	6	97.1106	0.08988	45.0	0.01304	287.0	1943.0	6578.0	

Table 6.86: *Top-5 results for SHS9K fusing models using SNF.*

6.9.3 Discussion

The best results obtained with each dataset are: Covers80 best **MR** equals to 23.73125; YouTubeCovers best **MR** equals to 7.63428571; Covers1000 best **MR** equals to 93.464; SHS9K best **MR** equals to 38.61393 (all of them using the mean function). It was unexpected to see that **SNF** does not perform well in this experiment settings for these datasets, since it is such a complex fusion function. The models fused to obtain each one of these results are:

- Covers80

- bass: $\{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean\}$
- drums: $\{chroma_stft, diff_stats_1, cosine_distance_oti\}$
- vocals: $\{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean\}$
- other: $\{zero_crossing_rate, basic_stats_1, chebyshev_distance\}$

- YouTubeCovers

- bass: $\{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean\}$
- drums: $\{chroma_stft, diff_stats_1, cosine_distance_oti\}$
- vocals: $\{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean\}$
- other: $\{pitch_contour_segmentation, markov_chain, circular_cosine\}$

- Covers1000

- bass: $\{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean\}$
- drums: $\{beat_synchronous_chroma_stft, diff_stats_1, cosine_distance_oti\}$
- vocals: $\{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean\}$
- other: $\{rhythm_histogram, bypass, cosine_distance\}$

- SHS9K

- bass: $\{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean\}$

- drums: $\{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean\}$
- vocals: $\{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean\}$
- other: $\{rhythm_histogram, bypass, cosine_distance\}$

Regarding the features from the models of “bass” and “vocals” best results, all of them have Pitch Contour Segmentation. Actually, if we look further, the models for the “bass” and “vocals” that lead to the best results are all the same: $\{pitch_contour_segmentation, octave_abstraction, lcs_circular_mean\}$. Tonal models are expected to appear in such positions, but the fact that they are all equal is quite surprising.

Analysing the remaining sources, the drums’ models from Covers80 and YouTubeCovers are exactly the same. The drums’ model from the Covers1000 is almost the same: the only difference is the feature being synchronized to beats. SHS9K, however, has a distinct model, the only resemblance is the tonal feature.

Finally, inspecting the models from the “other” source we have a vast group. However, this is expected since this source is the remaining of the separation process after excluding the bass, drums, and vocals from the full mix. So it can vary very much, according to the nature of the tracks of each dataset.

6.10 Experiment #7: Theoretical performance bounds

At this point, we have seen how our music similarity models perform on 5 CSI datasets, and we wish to compare our results with other CSI algorithms. For instance, it is possible to find on GitHub³² implementations of five important CSI algorithms: FTM2D [ET12], SiMPle [SYB⁺16], Serra09 [SSA09], LateFusionChen [CLX17], and EarlyFusionTraile [Tra17]. Table 6.87 shows the results from the algorithms we managed to run so far with our 5 selected CSI datasets.

algorithm	dataset	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
FTM2D	Covers80	26.3	0.476	3	0.476	64	105	144	160
SiMPle	Covers80	28.2	0.444	6.5	0.444	62	88	145	160
Serra09	Covers80	17.6	0.69	1	0.69	101	125	148	160
LateFusionChen	Covers80	15	0.709	1	0.709	107	125	152	160
EarlyFusionTraile	Covers80	9.19	0.759	1	0.759	116	132	157	160
FTM2D	YouTubeCovers	8.74	0.774	1	0.498	257	303	342	350
SiMPle	YouTubeCovers	7.59	0.786	1	0.484	256	315	344	350
Serra09	YouTubeCovers	5.47	0.919	1	0.751	317	331	347	350
FTM2D	Covers1000	71.4	0.439	5	0.368	372	569	826	1000
SiMPle	Covers1000	91.5	0.458	5	0.391	404	564	767	1000
Serra09	Covers1000	61.6	0.749	1	0.677	720	800	874	1000
FTM2D	Mazurkas	10.9	0.843	1	0.422	2190	2540	2680	2740
Serra09	Mazurkas	7.79	0.96	1	0.91	2590	2700	2720	2730
FTM2D	SHS9K	43.3	0.436	5	0.106	3220	5740	8370	9250

Table 6.87: Results obtained so far with 5 important CSI algorithms whose implementations are found in GitHub.

Comparing our results with the state-of-the-art, we verify that there is still room for improvement, especially with Covers1000, the dataset for which the applied models obtained the worst results. The low performance of our approach on this dataset led us to question the idea of attempting to solve the CSI problem for a whole dataset using a unique similarity model, which we termed “one-size-fits-all”.

Our current hypothesis is that this problem is not due to the discriminating power of the individual similarity models, but to the fact that the type of similarity between a song and its versions changes according to the musical decisions involved in writing/arranging each version. For instance, one cover song could keep the melody and change the harmony or the rhythm with respect to the original song, whereas another version might keep the rhythm and change a singing voice for a spoken one. This led us to conjecture that a similarity model should be selected for each specific query song, or even for each query and potential version candidate.

³²<https://github.com/>

In order to further investigate this we hypothesize the existence of an oracle that is capable of choosing the best possible model for each CSI query. In our previous experiments, each query produces a ranked list which corresponds to the similarity values of the query with respect to each other song within a chosen model. The hypothesized oracle should be able to instantly select the model that would place the first version of the query in the lowest possible rank of the corresponding list. The idea is to determine some type of upper bound for the performance of models within the context of our framework, and based on this upper bound to decide whether it would be beneficial to explore model selection techniques that would decide, based on a given query, which similarity model is most likely to produce good results. This will guide further research on model selection strategies for similarity-based music retrieval tasks.

An extra experiment is proposed, using the same 690 music similarity models, in order to assess the best possible outcome of these models, given the above-mentioned oracle³³. For each CSI dataset, we loop over all possible queries, and for each query we use best possible model provided by the oracle, thus producing a ranked list where the first retrieved cover appears at the earliest possible position. We then group all queries that produced the same rank, in order to understand the statistical distribution of the rank values and also to obtain a Mean Rank estimate for the theoretical algorithm proposed. Tables 6.88 to 6.92 display the rank distribution for all datasets considered, and Table 6.93 shows the corresponding Mean Ranks, alongside the MR values obtained in Experiment #2 for comparison.

rank (1st cover retrieved)	number of tracks	percentage
1	142	88.75
2	8	5.0
3	2	1.25
4	4	2.5
5	1	0.625
6	1	0.625
14	1	0.625
18	1	0.625

Table 6.88: Rank distribution for the Covers80 dataset.

rank (1st cover retrieved)	number of tracks	percentage
1	350	100.0

Table 6.89: Rank distribution for the YouTubeCovers dataset.

It is clear from these tables that, with the help of such an oracle, it is indeed possible to obtain very good results for the majority of queries. For instance, on YouTubeCovers the theoretical algorithm proposed achieves a perfect score where all queries produce a cover in the first rank of the retrieved list. Even the worst results attained by this algorithm, in the Covers1000 dataset, with the smallest percentage of queries producing a rank of 1 and a distribution with the longest tail, ends up with a Mean Rank of 1.709, which is impressive.

Although unrealistic, these numbers offer scientific evidence that the family of similarity models considered include very good combinations of features, aggregators and distances that are capable, in principle, of identifying covers with excellent performance. The question that remains open is how to identify such models that are perfectly fit for a given query.

In an attempt to devise a more realistic approach to help future heuristics identifying fitting models for input queries, we investigated how many different models would be required by such a heuristic in order to keep the mean rank close to the oracle's ideal. The underlying assumption here is that this model selection problem could be cast as a classification problem, where a trained

³³In this experiment, the oracle is implemented via a brute-force search over all available models.

rank (1st cover retrieved)	number of tracks	percentage
1	811	81.1
2	86	8.6
3	30	3.0
4	13	1.3
5	12	1.2
6	9	0.9
7	7	0.7
8	6	0.6
9	3	0.3
10	3	0.3
11	7	0.7
12	3	0.3
13	3	0.3
16	3	0.3
19	1	0.1
24	1	0.1
31	1	0.1
42	1	0.1

Table 6.90: *Rank distribution for the Covers1000 dataset.*

rank (1st cover retrieved)	number of tracks	percentage
1	2738	99.89055089383437
2	3	0.10944910616563298

Table 6.91: *Rank distribution for the Mazurkas dataset.*

classifier would be able to predict the best model for each query within a small set of choices. We conducted a secondary theoretical experiment exploring the number of models required to produce the theoretical best results for a certain fraction of the dataset.

The complete list of models is sorted in descending order by the number of tracks for which they produce the best possible rank. We consider subsets of the n first models in this list. For each n , we compute the theoretical mean rank with a restricted version of the oracle that selects the best among the available models, as well as the number of tracks in the dataset for which this selection is optimal. We then plot, for each dataset, the number of tracks optimally covered as well as the theoretical mean rank attained as functions of n . Figures 6.19-6.23 display these results.

In these Figures it is possible to observe that the mean rank values drop abruptly with the addition of very few similarity models. Even for the Covers1000 dataset, which attained the worst metrics with a single model, the mean rank obtained in Experiment #2 drops from 144.041 to 72.0205 with the use of 4 models, and to 36.01025 with 8 models.

This theoretical experiment is meant as an abstract exercise to explore the limits of an approach based on the class of similarity models that use the pipeline described in Section 5.1. It allows us to conclude that such an approach is capable of producing very good results, if extended beyond the “one-size-fits-all” assumption that underlies this research.

rank (1st cover retrieved)	number of tracks	percentage
1	9133	98.35235838897265
2	127	1.3676502261468877
3	19	0.20460908895110919
4	6	0.0646133965108766
6	1	0.010768899418479432

Table 6.92: Rank distribution for the SHS9k dataset.

dataset	best mean rank from experiment #2	oracle's theoretical mean rank
Covers80	41.575	1.39375
YouTubeCovers	7.97143	1.0
Covers1000	144.041	1.709
Mazurkas	4.15724	1.0010944910616564
SHS9K	47.57883	1.0202455309067413

Table 6.93: Comparison of metrics obtained in Experiment #2 with the theoretical metrics.

Figure 6.19: Number of tracks and theoretical mean rank as functions of the number of models for the Covers80 dataset.

Figure 6.20: Number of tracks and theoretical mean rank as functions of the number of models for the YouTubeCovers dataset.

Figure 6.21: Number of tracks and theoretical mean rank as functions of the number of models for the Covers1000 dataset.

Figure 6.22: Number of tracks and theoretical mean rank as functions of the number of models for the Mazurkas dataset.

Figure 6.23: Number of tracks and theoretical mean rank as functions of the number of models for the SHS9k dataset.

Chapter 7

Conclusions

In this final Chapter, the best results for every **Cover Song Identification (CSI)** experiment are recalled in Tables 7.1 to 7.5. Remembering that Mazurkas is not used in Experiment #6 (since it is not possible to extract the four individual sources), and that SHS9K is only used as training dataset in Experiments #4a and #4b.

Covers80

	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
experiment #2	41.575	0.19359	31.0	0.19359	21.0	46.0	142.0	160.0
experiment #4a	33.97812	0.28545	16.25	0.28545	34.8	62.8	145.0	160.0
experiment #4b	33.33313	0.2385	19.4	0.2385	24.1	64.6	147.8	160.0
experiment #5	41.3	0.20834	22.5	0.20834	20.0	61.0	134.0	160.0
experiment #6	23.73125	0.41531193	10.0	0.41531193	57.0	83.0	152.0	160.0

Table 7.1: Best results for Covers80 through all CSI experiments.

YouTubeCovers

	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
experiment #2	7.97143	0.6942	1.0	0.36114	219.0	296.0	345.0	350.0
experiment #4a	13.42257	0.50354	3.0	0.21716	138.4	258.9	345.0	350.0
experiment #4b	5.63714	0.70923	1.0	0.39507	221.9	306.2	348.9	350.0
experiment #5	8.18857	0.66438	1.0	0.34196	202.0	300.0	346.0	350.0
experiment #6	7.63428571	0.648763101	1.0	0.331591159	196.0	286.0	346.0	350.0

Table 7.2: Best results for YouTubeCovers through all CSI experiments.

Covers1000

	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
experiment #2	144.041	0.25731	35.0	0.19159	201.0	366.0	636.0	1000.0
experiment #4a	146.5084	0.17431	42.35	0.12918	103.9	311.0	615.2	1000.0
experiment #4b	109.0794	0.30175	16.5	0.23293	228.7	440.0	707.0	1000.0
experiment #5	139.806	0.27382	30.0	0.20739	218.0	381.0	662.0	1000.0
experiment #6	93.464	0.437937535	7.0	0.357714675	385.0	537.0	779.0	1000.0

Table 7.3: Best results for Covers1000 through all CSI experiments.

Mazurkas

	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
experiment #2	4.15724	0.95774	1.0	0.82286	2561.0	2714.0	2728.0	2739.0
experiment #4a	3.99186	0.92073	1.0	0.44795	2419.5	2685.7	2726.0	2740.0
experiment #4b	1.97322	0.93372	1.0	0.62158	2457.3	2697.8	2734.5	2741.0
experiment #5	2.81284	0.92509	1.0	0.55828	2434.0	2690.0	2727.0	2740.0

Table 7.4: Best results for Mazurkas through all CSI experiments.

SHS9K

	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
experiment #2	47.57883	0.40387	6.0	0.05102	3008.0	5188.0	8067.0	9265.0
experiment #5	43.30401	0.43289	5.0	0.05862	3289.0	5433.0	8182.0	9278.0
experiment #6	38.613935	0.463884786	4.0	0.0697890851	3581.0	5727.0	8291.0	9276.0

Table 7.5: Best results for SHS9K through all CSI experiments.

7.1 Analysing the Results and Recalling the Goals

From Tables 7.1 to 7.5 above it is possible to see that every dataset has improved results with at least one experiment, compared to experiment #2 (which is our base experiment). This is an encouraging outcome of our proposed approaches and methodology for the CSI problem.

Music Similarity and Cover Song Identification

Regarding each individual experiment, #1 and #2 are, to the author’s knowledge, the first attempt to benchmark music similarity models, where several models not considered in the literature are tested. Moreover, several comparative conclusions are obtained: we should apply [Optimal Transition Index \(OTI\)](#) to chromagrams, not add minimum and maximum values to single Gaussian aggregators, consider the feature differences for single Gaussian aggregators, among others.

The main goal of experiments #1 and #2 is to check which music similarity models lead to best results for the annotated datasets, whether with generic datasets used in Experiment #1 or CSI datasets in Experiment #2, and this is completely accomplished.

Cover Song Classification

Experiment #3 presents a new heuristic for train/test split for the [Cover Song Classification \(CSC\)](#) problem, a unique way of building samples (by the fusion of similarity matrices obtained by distinct models), and performs binary classification with 5 datasets and 5 classifiers (several combinations not published before). The goals include verifying which model combination scheme lead to the best results, and if our suggestion to use filtered models (skipping equivalent ones) achieves the best results (which is indeed observed).

Experiment #4 tests our proposal to exploit trained classifiers to build new similarity matrices, and to return to the CSI problem. The main goal of this experiment is to check if it possible to improve CSI results using the matrices manufactured by CSC runs. Here again the use of filtered models to build samples lead to better results than using the Top-N models, and indeed better results are reached for every CSI dataset.

Dataset Modifications

Also to the author’s knowledge, Experiment #5 is the first attempt to explore different types of dataset modifications together in a comparative study to investigate how they affect music similarity metrics. The main goal of this experiment is to verify if any modification leads to better CSI results when compared to the metrics obtained with the original datasets. Whether comparing [Mean Rank \(MR\)](#) or [Mean Average Precision \(MAP\)](#), the most important metrics for the CSI problem, every dataset presented at least one modification that lead to a better result. The frame selection secondary datasets are the most prominent ones, and our proposal of using the [Root Mean Square \(RMS\)](#) values of the isolated vocals (instead of the RMS values of the original mixes) achieves better metrics.

Fusion

Experiment #6 uses four distinct functions to fuse music similarity matrices obtained from the modified datasets by source separation. The goal of this experiment is to verify if it is possible to

achieve better results when compared to the original dataset alone. This indeed is verified by the experiment that lead to better MR values for all datasets.

Theoretical performance bounds

After comparing the best results obtained for each dataset (as displayed in Table 7.6) with the state-of-the-art, we investigated and concluded that the problem lies on the attempt to solve the CSI problem for a whole dataset using a unique similarity model (the “one-size-fits-all” approach), rather than on the discriminating power of the individual similarity models. Experiment #7 provides scientific evidence that the family of similarity models considered in this project are capable of identifying covers with excellent performance.

dataset	best MR	experiment
Covers80	23.73125	#6
YouTubeCovers	5.63714	#4b
Covers1000	93.464	#6
Mazurkas	1.97322	#4b
SHS9K	38.613935	#6

Table 7.6: *The best results obtained for each CSI dataset.*

7.2 Future work

Every one of these experiments still has space for improvements. In this Section we discuss our future work plans.

Music Similarity and Cover Song Identification

The list of improvements for Experiments #1 and #2 includes the expansion of the extractors (HPCP, crema-PCP, Onset Patterns, Scale Transform, Pitch Bihistogram, Intervalgram, etc), aggregators (Dynamic Time Warping (DTW), Self-Organizing Map (SOM), vector quantization using tree-based clustering, n-grams, etc), and distances (Mahalanobis, Jensen-Shannon, Smith-Waterman, Mongeau-Sankoff, etc) for the music similarity framework.

Modules of the music similarity framework can also be expanded with approaches not currently contemplated. For instance, the extractor module can be extended with feature learning techniques [PBD⁺16, YXCY20], and the distance module can benefit with the use of metric learning techniques [SWW08, HKKL17].

Cover Song Classification

Experiments #3 and #4 can be further explored with different models to be fused, alternative ways to build samples, new classifiers (such as SVM, KNN-based, neural networks, etc) and more parameters for classifiers. We would like also to try in the future the python toolkit called `auto-sklearn`¹ that can perform automated algorithm selection and hyperparameter tuning. Particularly in experiment #4 we wish to train classifiers with a larger dataset in order to collect metrics for SHS9K.

Dataset Modifications

Regarding Experiment #5 we have a vast list of possible future improvements, from variations on the settings of the current techniques (frames with more samples, segments with variable duration values, etc) to the adoption of new techniques (alternative segmentation, thumbnailing, or source

¹<https://automl.github.io/auto-sklearn/master/>

separation algorithms). The latter has a very good candidate, Spleeter [HKVM20] by Deezer², that can separate the tracks into 5 stems: vocals, drums, bass, piano, and other.

Also, we desire to integrate at least one method that compares the sets of segments when comparing two songs A and B . For instance, this can be done similarly to what Bozzon et al. [BPVT08] propose, using a graph that contains the distances from all segments of song A to all the segments of song B , and explore this graph in order to reduce it to a unique distance value.

Fusion

The sixth experiment is also full of potential. The fusion can be done using matrices from other modified datasets of Experiment #5 (besides only the source separation ones). It can be also done using matrices build in Experiment #4. We can fusion virtually any similarity matrix obtained for a CSI dataset, even inter-experiments matrices, and matrices obtained by other algorithms than our own.

Theoretical performance bounds

Lastly, Experiment #7 encourages us to investigate how to identify the music similarity models that are perfectly fit for a given query. As mentioned in Section 6.10 one idea is to cast the problem as a classification one, where a trained classifier would be able to predict the best model for each query. The design of classification strategies for selecting appropriate similarity models (music perspectives) for identifying versions of a given query is the subject of future work.

²<https://www.deezer.com/>

Appendix A

Music Similarity: best models per class

Ballroom

class	iicsr	extractor	aggregator	distance
ChaChaCha	1.546925946371605	melspectrogram	gaussian_mixture_model_default	cosine_distance
Jive	1.440056195358931	spectral_bandwidth	vector_quantization	cosine_distance
Quickstep	1.2568875004786253	mfcc	vector_quantization	cosine_distance
Rumba-American	1.9796567522114297	spectral_flatness	diff_stats_2	chebyshev_distance
Rumba-International	1.5337427656322973	chroma_cens	diff_stats_2	chebyshev_distance_oti
Rumba-Misc	1.4688978853570556	spectral_flatness	diff_stats_2	chebyshev_distance
Samba	1.7050151994083254	melspectrogram	gaussian_mixture_model_default	cosine_distance
Tango	1.3269934151838436	spectral_rolloff	vector_quantization	cosine_distance
VienneseWaltz	1.3527489891887357	spectral_rolloff	vector_quantization	cosine_distance
Waltz	1.585048971827175	spectral_flatness	vector_quantization	manhattan_distance

GTZAN

class	iicsr	extractor	aggregator	distance
blues	2.0634199115352496	spectral_contrast	vector_quantization	cosine_distance
classical	2.644307967413323	melspectrogram	vector_quantization	manhattan_distance
country	1.2617036717897034	spectral_contrast	vector_quantization_default	cosine_distance
disco	1.4027194091593116	melspectrogram	gaussian_mixture_model_default	cosine_distance
hiphop	1.719408802575485	melspectrogram	gaussian_mixture_model_default	cosine_distance
jazz	1.3459618632721098	spectral_contrast	vector_quantization	cosine_distance
metal	3.187620155034533	spectral_contrast	vector_quantization	cosine_distance
pop	2.7107378150455474	spectral_contrast	vector_quantization	cosine_distance
reggae	1.3653166221767408	melspectrogram	statistical_summarization	cosine_distance
rock	1.1913570919251713	spectral_bandwidth	vector_quantization	cosine_distance

IOACAS-QBH

class	iicsr	extractor	aggregator	distance
00024	1.931033773676616	mfcc	vector_quantization	cosine_distance
00025	1.901487447845127	mfcc	vector_quantization	cosine_distance
00065	1.6718779950388922	chroma_cqt	gaussian_mixture_model_default	euclidean_distance
00075	1.2647310006280135	pitch_contour_segmentation	markov_chain	circular_cosine
00080	2.0424897695993898	tonnetz	gaussian_mixture_model_default	chebyshev_distance
00083	1.4697457241534404	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
00089	1.3488308166318899	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00101	1.706905481098727	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
00106	1.4425725406149095	mfcc	vector_quantization	cosine_distance
00108	1.7193037170909928	melspectrogram	gaussian_mixture_model_default	cosine_distance
00110	1.400753203469558	beat_synchronous_chroma_stft	gaussian_mixture_model_default	chebyshev_distance
00111	1.7994128763939803	tonnetz	gaussian_mixture_model_default	chebyshev_distance
00114	1.6178691674810624	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
00116	2.960345510079841	chroma_stft	gaussian_mixture_model_default	chebyshev_distance
00120	2.0047212679696647	mfcc	vector_quantization	cosine_distance
00128	1.436903729562698	chroma_stft	gaussian_mixture_model_default	chebyshev_distance
00129	1.5756637211240436	chroma_cens	gaussian_mixture_model_default	chebyshev_distance
00133	1.698328767142286	melspectrogram	statistical_summarization	cosine_distance
00139	1.5321662211203018	melspectrogram	vector_quantization	cosine_distance
00140	1.5673438296221571	pitch_contour_segmentation	interval_abstraction	lcs_min
00160	1.3946192661995784	tonnetz	gaussian_mixture_model_default	cosine_distance
00162	1.7709617258242663	mfcc	vector_quantization	cosine_distance
00167	1.799982100675112	pitch_contour_segmentation	interval_abstraction	lcs_min
00185	1.6031910027744627	melspectrogram	gaussian_mixture_model_default	cosine_distance
00192	1.6328450865612627	chroma_cqt	gaussian_mixture_model_default	chebyshev_distance
00193	1.91270620701724	mfcc	vector_quantization	cosine_distance
00195	1.7381033411120395	pitch_contour_segmentation	interval_abstraction	levenshtein_max
00197	1.598649434779093	melspectrogram	gaussian_mixture_model_default	cosine_distance
00210	1.4270926614362023	pitch_contour_segmentation	interval_abstraction	lcs_min
00232	1.5986903612139411	melspectrogram	gaussian_mixture_model_default	cosine_distance
00233	1.543336613016316	pitch_contour_segmentation	interval_abstraction	lcs_min
00245	1.6270473736295192	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
00250	1.5896671948964811	beat_synchronous_chroma_cqt	vector_quantization	cosine_distance

00265	1.584513545767764	melspectrogram	vector_quantization	cosine_distance
00271	1.4883022097908574	tonnetz	gaussian_mixture_model_default	chebyshev_distance
00276	1.71686444066104	mfcc	vector_quantization	cosine_distance
00278	1.438752643998202	tonnetz	gaussian_mixture_model_default	cosine_distance
00279	1.389129307559736	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
00289	1.9877068860786522	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
00293	1.567867210929537	melspectrogram	gaussian_mixture_model_default	cosine_distance
00306	1.5380683202702634	mfcc	vector_quantization	cosine_distance
00319	1.7075076316335294	mfcc	vector_quantization	cosine_distance
00321	1.6198335795775	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
00362	1.7106640953552243	beat_synchronous_chroma_cens	vector_quantization	cosine_distance
00363	1.4609006885924525	melspectrogram	gaussian_mixture_model_default	cosine_distance
00392	1.5160656733542792	melspectrogram	gaussian_mixture_model_default	cosine_distance
00399	2.256539583353676	melspectrogram	gaussian_mixture_model_default	cosine_distance
00438	1.6025762751801291	pitch_contour_segmentation	octave_abstraction	lcs_circular_min
00461	1.4200736016009579	pitch_contour_segmentation	octave_abstraction	lcs_circular_min
00468	2.670688648585469	beat_synchronous_chroma_cens	vector_quantization	cosine_distance
00475	2.0395366298376656	melspectrogram	gaussian_mixture_model_default	cosine_distance
00513	1.4490040148250403	mfcc	vector_quantization	cosine_distance
00514	1.5969087161067088	mfcc	vector_quantization	cosine_distance
00515	1.669215886725964	mfcc	vector_quantization	cosine_distance
00529	1.2959951770723588	mfcc	vector_quantization	cosine_distance
00533	1.2588969688658502	pitch_contour_segmentation	interval_abstraction	levenshtein_max
00540	2.223344643337316	melspectrogram	gaussian_mixture_model_default	cosine_distance
00550	1.742149003174559	beat_synchronous_chroma_cqt	gaussian_mixture_model_default	chebyshev_distance
00561	1.3144417901219627	chroma_cens	gaussian_mixture_model_default	chebyshev_distance
00562	1.1864465193878866	pitch_contour_segmentation	pitch_contour_5_levels	lcs_min
00568	2.066951474498263	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
00570	1.457807480606345	mfcc	vector_quantization	cosine_distance
00572	1.3061070679274152	chroma_stft	gaussian_mixture_model_default	chebyshev_distance
00573	1.9717250385878164	melspectrogram	gaussian_mixture_model_default	cosine_distance
00594	1.3437688616402435	pitch_contour_segmentation	octave_abstraction	lcs_circular_min
00606	1.2092636365643834	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
00628	2.3701760197379	mfcc	vector_quantization	cosine_distance
00636	1.3322891503508387	pitch_contour_segmentation	interval_abstraction	lcs_min
00643	1.4545261625892711	spectral_contrast	vector_quantization	cosine_distance
00647	1.778928833629243	pitch_contour_segmentation	interval_abstraction	levenshtein_max
00660	1.6974224710529804	beat_synchronous_chroma_cens	vector_quantization	cosine_distance
00662	1.426064054668703	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
00685	1.7764138167778094	beat_synchronous_chroma_stft	vector_quantization	manhattan_distance
00693	2.1406522959772785	melspectrogram	gaussian_mixture_model_default	cosine_distance
00728	1.3546927851858757	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
00730	2.3015061276939672	melspectrogram	gaussian_mixture_model_default	cosine_distance
00732	2.66511950555689	melspectrogram	statistical_summarization	cosine_distance
00736	1.6642607085207062	pitch_contour_segmentation	interval_abstraction	lcs_min
00747	1.553524826402716	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
00770	1.3064622022631687	beat_synchronous_chroma_stft	gaussian_mixture_model_default	chebyshev_distance
00790	1.5820940282043419	mfcc	vector_quantization	cosine_distance
00794	1.3985104243217703	beat_synchronous_chroma_cens	gaussian_mixture_model_default	chebyshev_distance
00805	1.481443188415013	mfcc	vector_quantization	manhattan_distance
00811	2.33499966215805	melspectrogram	vector_quantization	cosine_distance
00839	1.8660756823280418	melspectrogram	gaussian_mixture_model_default	cosine_distance
00850	1.4261636071632458	pitch_contour_segmentation	interval_abstraction	lcs_min
00858	3.4822001999089216	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
00914	1.4062394853563454	chroma_stft	gaussian_mixture_model_default	euclidean_distance
00915	2.1217294472660932	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
00926	1.2171414140334174	pitch_contour_segmentation	octave_abstraction	lcs_circular_min
00937	1.38184131861926	beat_synchronous_chroma_cqt	vector_quantization	manhattan_distance
00941	1.8209659393141526	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
00956	1.9085132062621768	melspectrogram	gaussian_mixture_model_default	cosine_distance
01000	1.6846627033816302	pitch_contour_segmentation	interval_abstraction	lcs_min
01014	2.54163085546414	spectral_bandwidth	gaussian_mixture_model_default	cosine_distance
01036	1.6123391573236878	pitch_contour_segmentation	interval_abstraction	lcs_min
01039	1.5688057701421279	spectral_bandwidth	gaussian_mixture_model_default	cosine_distance
01044	1.6097343380657871	melspectrogram	gaussian_mixture_model_default	cosine_distance
01054	1.7431166191868042	chroma_stft	gaussian_mixture_model_default	chebyshev_distance
01062	1.3566519357943665	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
01067	1.8049895339591098	chroma_cqt	gaussian_mixture_model_default	chebyshev_distance
01068	1.644661748696255	beat_synchronous_chroma_cqt	gaussian_mixture_model_default	chebyshev_distance
01070	1.5723284869377947	mfcc	vector_quantization	cosine_distance
01082	2.2659646107636866	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
01083	1.5676594928297984	spectral_rolloff	gaussian_mixture_model_default	cosine_distance
01094	1.660274410378681	melspectrogram	gaussian_mixture_model_default	cosine_distance
10013	1.8031759583321743	statistical_spectrum_descriptor	bypass	cosine_distance
10021	1.5234895758879832	pitch_contour_segmentation	markov_chain	circular_cosine
10024	1.6304024448640126	spectral_bandwidth	gaussian_mixture_model_default	cosine_distance
10027	2.2349177233420887	melspectrogram	statistical_summarization	cosine_distance
10030	1.976956856190364	melspectrogram	gaussian_mixture_model_default	cosine_distance
10032	1.573195286663101	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
10039	2.6700383195270123	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
10040	1.5508642475570744	pitch_contour_segmentation	interval_abstraction	lcs_max
10043	1.7755426890197479	statistical_spectrum_descriptor	bypass	cosine_distance
10045	1.6733617919241075	melspectrogram	vector_quantization_default	cosine_distance
10052	1.5271202403969473	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
10070	1.7487902488208227	beat_synchronous_chroma_cens	gaussian_mixture_model_default	chebyshev_distance
10075	1.3188128796022793	chroma_stft	gaussian_mixture_model_default	chebyshev_distance
10082	1.316564824522289	beat_synchronous_chroma_stft	gaussian_mixture_model_default	chebyshev_distance
10083	2.7762200253734437	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
10084	1.537132972230257	pitch_contour_segmentation	interval_abstraction	lcs_min
10095	1.8975263472026556	melspectrogram	statistical_summarization	cosine_distance
10109	2.590245141536958	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
10110	1.8365597527229036	beat_synchronous_chroma_cqt	vector_quantization	cosine_distance
10136	1.5366828819468823	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
10142	1.4315222427410381	pitch_contour_segmentation	interval_abstraction	levenshtein_max
10143	1.6813297055122471	spectral_bandwidth	gaussian_mixture_model_default	cosine_distance
10150	2.673506140607402	spectral_bandwidth	gaussian_mixture_model_default	cosine_distance
10153	1.5097424504449755	mfcc	vector_quantization	cosine_distance
10157	1.938998784908532	statistical_spectrum_descriptor	bypass	cosine_distance
10160	1.5319087253134673	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
10164	2.0512153305863747	statistical_spectrum_descriptor	bypass	cosine_distance
10169	1.3870887349025844	tonnetz	gaussian_mixture_model_default	chebyshev_distance

10173	1.40888162209837	melspectrogram	vector_quantization	cosine_distance
10183	1.6076388010800153	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
10186	2.7663688067746244	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
10196	1.745295866553635	pitch_contour_segmentation	interval_abstraction	lcs_min
10204	2.511697571571461	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
10209	1.6695775951188168	pitch_contour_segmentation	interval_abstraction	lcs_min
10220	6.6664838256588785	melspectrogram	gaussian_mixture_model_default	cosine_distance
10222	2.373718824769523	chroma_stft	gaussian_mixture_model_default	chebyshev_distance
10223	1.3412999798625447	pitch_contour_segmentation	interval_abstraction	levenshtein_max
10227	1.5279188065497633	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
10230	1.719142224660351	spectral_centroid	gaussian_mixture_model_default	cosine_distance
10231	1.3477355744393593	chroma_cqt	gaussian_mixture_model_default	euclidean_distance
10237	1.9704596548284965	chroma_stft	gaussian_mixture_model_default	chebyshev_distance
10251	2.769220761200123	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
10254	1.5323379659784537	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
10255	1.3533636113070917	zero_crossing_rate	gaussian_mixture_model_default	cosine_distance
10257	2.988035414397908	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
10258	1.3401408486384718	beat_synchronous_chroma_cqt	gaussian_mixture_model_default	chebyshev_distance
10263	1.6641893151902698	pitch_contour_segmentation	interval_abstraction	lcs_min
10266	1.8018945834085849	chroma_stft	gaussian_mixture_model_default	euclidean_distance
10272	2.756024488179296	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
10274	1.5144212736951403	spectral_contrast	vector_quantization	cosine_distance
10285	1.6099899438392196	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
10291	1.4780701344829883	chroma_stft	gaussian_mixture_model_default	chebyshev_distance
10294	2.9038263543029452	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
10295	1.5581485419502679	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
10298	1.456357575354308	tonnetz	statistical_summarization	cosine_distance
10300	1.5028123090526297	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
10302	1.7178068115878014	melspectrogram	gaussian_mixture_model_default	cosine_distance
10303	1.643511082683424	mfcc	vector_quantization	cosine_distance
10304	2.43098932076452	spectral_bandwidth	gaussian_mixture_model_default	cosine_distance
10306	1.8911515811625417	pitch_contour_segmentation	interval_abstraction	lcs_min
10310	1.7274132114889453	melspectrogram	gaussian_mixture_model_default	cosine_distance
10312	1.630677818567374	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
10314	1.4927312317267682	chroma_cqt	gaussian_mixture_model_default	chebyshev_distance
10325	1.806610736255341	mfcc	vector_quantization	cosine_distance
10329	1.5766901845760417	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
10331	1.5816827117829836	beat_synchronous_chroma_stft	gaussian_mixture_model_default	euclidean_distance
10332	2.6188891770030245	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
10340	1.3901279920961627	chroma_stft	gaussian_mixture_model_default	chebyshev_distance
10341	1.5273397406011338	beat_synchronous_chroma_stft	gaussian_mixture_model_default	chebyshev_distance
10343	3.3538335226166898	mfcc	vector_quantization	cosine_distance
10345	2.2300102100355916	spectral_bandwidth	gaussian_mixture_model_default	cosine_distance
10354	1.4448355992220743	chroma_cens	vector_quantization	cosine_distance
10370	1.6506145936162089	pitch_contour_segmentation	interval_abstraction	levenshtein_max
10372	1.5902382411784608	mfcc	vector_quantization	cosine_distance
10382	1.6337097456117633	melspectrogram	gaussian_mixture_model_default	cosine_distance
10383	2.326723300626564	spectral_bandwidth	gaussian_mixture_model_default	cosine_distance
10399	1.6307156671730356	pitch_contour_segmentation	interval_abstraction	lcs_min
10404	1.6658829861244748	mfcc	vector_quantization	cosine_distance
10412	1.633439172987491	beat_synchronous_chroma_cqt	gaussian_mixture_model_default	chebyshev_distance
10430	1.9303340435202792	mfcc	vector_quantization	cosine_distance
10435	1.298987798068178	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
10437	1.6907215914040645	beat_synchronous_chroma_stft	gaussian_mixture_model_default	chebyshev_distance
10442	1.958619801094365	mfcc	vector_quantization	cosine_distance
10445	1.6670816361105545	pitch_contour_segmentation	interval_abstraction	lcs_min
10446	2.6071473651721258	beat_synchronous_chroma_cens	vector_quantization	cosine_distance
10447	1.6503733090503572	pitch_contour_segmentation	interval_abstraction	levenshtein_max
10453	1.6307144432291583	beat_synchronous_chroma_cqt	gaussian_mixture_model_default	chebyshev_distance
10477	2.0465638148683643	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
10478	1.8298612382962005	chroma_cens	vector_quantization	cosine_distance
10479	1.605006696430526	tonnetz	vector_quantization_default	manhattan_distance
10491	1.8393406113163555	beat_synchronous_chroma_cqt	gaussian_mixture_model_default	chebyshev_distance
10494	1.2802261157408032	tonnetz	statistical_summarization	cosine_distance
10503	1.525643690929738	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
10512	1.5023627702936215	chroma_stft	gaussian_mixture_model_default	cosine_distance
10520	1.7497136888081002	beat_synchronous_chroma_stft	gaussian_mixture_model_default	chebyshev_distance
10521	1.2701680775141684	spectral_contrast	vector_quantization	cosine_distance
10529	1.5066769087050793	mfcc	vector_quantization	cosine_distance
10541	1.240651266466125	chroma_cens	vector_quantization	cosine_distance
10546	1.9340688364268341	beat_synchronous_chroma_cens	vector_quantization	manhattan_distance
10567	1.5769625001697865	chroma_cqt	gaussian_mixture_model_default	chebyshev_distance
10583	1.6621578166850806	chroma_cens	gaussian_mixture_model_default	chebyshev_distance
10594	1.934582370662252	mfcc	vector_quantization	cosine_distance
10606	2.028325575503405	spectral_bandwidth	gaussian_mixture_model_default	cosine_distance
10611	1.4900579714482276	pitch_contour_segmentation	interval_abstraction	lcs_min
10613	1.7565730125955301	beat_synchronous_chroma_cqt	vector_quantization	cosine_distance
10617	1.6579914360927908	spectral_contrast	vector_quantization	cosine_distance
10628	1.2952872501491235	spectral_centroid	vector_quantization_default	chebyshev_distance
10642	1.6341991551161794	pitch_contour_segmentation	interval_abstraction	lcs_min
10985	1.5601756667287836	chroma_cqt	gaussian_mixture_model_default	chebyshev_distance
10989	2.9787331838475213	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
11007	1.6418619342691785	beat_synchronous_chroma_cens	vector_quantization_default	cosine_distance
11070	1.36617649261048	pitch_contour_segmentation	octave_abstraction	lcs_circular_min
11209	2.835494524090436	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
11228	4.637017841072229	melspectrogram	gaussian_mixture_model_default	cosine_distance
11299	1.5367149092967716	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
11342	1.6218561646113163	beat_synchronous_chroma_cens	vector_quantization	cosine_distance
11441	1.79236450430892	chroma_stft	gaussian_mixture_model_default	chebyshev_distance
11485	1.837985376249784	pitch_contour_segmentation	interval_abstraction	lcs_min
11488	1.833900137837313	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
11521	1.5169401341463162	tonnetz	statistical_summarization	cosine_distance
11566	1.6347424316914292	pitch_contour_segmentation	interval_abstraction	lcs_min
11591	1.7404129644795805	pitch_contour_segmentation	interval_abstraction	lcs_min
11620	1.521483989143152	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
11650	1.601884774605334	pitch_contour_segmentation	interval_abstraction	lcs_min
11657	2.144991384859208	statistical_spectrum_descriptor	bypass	cosine_distance
11682	3.711098176521339	melspectrogram	gaussian_mixture_model_default	cosine_distance
11710	1.6597745170769258	beat_synchronous_chroma_cqt	vector_quantization	cosine_distance
11719	1.5253920120123463	melspectrogram	statistical_summarization	cosine_distance
11739	2.7151715276746735	temporal_statistical_spectrum_descriptor	bypass	cosine_distance

11774	1.863559190424452	melspectrogram	statistical_summarization	cosine_distance
11789	2.0880554539614167	statistical_spectrum_descriptor	bypass	cosine_distance
11859	1.6468003010333088	beat_synchronous_chroma_cens	vector_quantization	cosine_distance
12008	2.097655988027231	chroma_stft	gaussian_mixture_model_default	chebyshev_distance
12040	1.601746282770355	beat_synchronous_chroma_stft	gaussian_mixture_model_default	euclidean_distance
12049	1.5897989330298716	pitch_contour_segmentation	interval_abstraction	lcs_min
12062	2.6866105595017338	melspectrogram	statistical_summarization	cosine_distance
12072	1.5579478919028142	beat_synchronous_chroma_cqt	gaussian_mixture_model_default	euclidean_distance
12082	1.3363786806169757	tonnetz	gaussian_mixture_model_default	cosine_distance
12093	5.264219610914226	chroma_cqt	gaussian_mixture_model_default	chebyshev_distance
12106	2.3679832008383137	melspectrogram	statistical_summarization	cosine_distance
12110	1.8875118669788526	melspectrogram	vector_quantization_default	cosine_distance
12113	1.3907428334628744	beat_synchronous_chroma_cqt	gaussian_mixture_model_default	chebyshev_distance
12117	1.8558153184424127	pitch_contour_segmentation	interval_abstraction	lcs_min
12177	3.45978689750222	spectral_flatness	gaussian_mixture_model_default	cosine_distance
12191	2.047937863470347	melspectrogram	gaussian_mixture_model_default	cosine_distance
12212	1.3466842908682706	spectral_contrast	vector_quantization	cosine_distance
12252	1.7105087432725972	chroma_stft	gaussian_mixture_model_default	chebyshev_distance
12263	1.8179304062805244	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
12270	19.081881671680264	spectral_flatness	gaussian_mixture_model_default	cosine_distance
12290	1.5627931597323883	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
12315	1.7160704573082097	chroma_cens	gaussian_mixture_model_default	chebyshev_distance
12320	1.8755768713999712	spectral_flatness	gaussian_mixture_model_default	cosine_distance
12321	2.9654811058076023	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
12340	1.6190211217418007	chroma_stft	gaussian_mixture_model_default	chebyshev_distance
12342	1.7794593451708427	pitch_contour_segmentation	interval_abstraction	lcs_min
12425	2.2719376928873576	statistical_spectrum_descriptor	bypass	cosine_distance
12434	3.9214781227454916	melspectrogram	gaussian_mixture_model_default	cosine_distance
12435	2.2523833268260374	statistical_spectrum_descriptor	bypass	cosine_distance
12453	1.528832935235234	spectral_flatness	gaussian_mixture_model_default	chebyshev_distance
12476	1.6690520151159296	pitch_contour_segmentation	interval_abstraction	lcs_min
12480	1.604631244445697	melspectrogram	statistical_summarization	cosine_distance
12485	1.7142355544066685	melspectrogram	statistical_summarization	cosine_distance
12503	1.6012689134526688	tonnetz	gaussian_mixture_model_default	cosine_distance
12539	1.3728812679545612	beat_synchronous_chroma_stft	gaussian_mixture_model_default	chebyshev_distance
12584	1.397753195802702	zero_crossing_rate	gaussian_mixture_model_default	cosine_distance
12591	3.476777901752074	melspectrogram	statistical_summarization	cosine_distance
12599	3.607006641919063	melspectrogram	statistical_summarization	cosine_distance
12617	3.196771607735613	melspectrogram	statistical_summarization	cosine_distance
12644	2.0455176123144554	melspectrogram	vector_quantization_default	cosine_distance
12648	2.242531788404855	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
12649	2.9808173519113623	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
12658	2.3386670317994622	beat_synchronous_chroma_stft	vector_quantization	manhattan_distance
12659	1.5706860069945892	melspectrogram	vector_quantization_default	cosine_distance
12663	3.2439630824636096	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
12667	1.7982780608673947	pitch_contour_segmentation	interval_abstraction	lcs_min
12691	3.580989502064679	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
12700	1.9090861086278557	statistical_spectrum_descriptor	bypass	cosine_distance
12701	1.5830039703665708	spectral_bandwidth	gaussian_mixture_model_default	cosine_distance
12706	1.7874059488096419	melspectrogram	vector_quantization_default	cosine_distance
12707	1.668777287243657	beat_synchronous_chroma_stft	vector_quantization_default	cosine_distance
12713	1.6640710017832863	pitch_contour_segmentation	interval_abstraction	lcs_min
12715	2.1378390143399275	melspectrogram	statistical_summarization	cosine_distance
12716	1.6471747733794804	melspectrogram	vector_quantization_default	cosine_distance
12734	1.7836348567438436	statistical_spectrum_descriptor	bypass	cosine_distance
12743	2.0234883184181474	statistical_spectrum_descriptor	bypass	cosine_distance
12744	2.026018596535022	beat_synchronous_chroma_cqt	vector_quantization	cosine_distance
12752	1.5213724868188667	spectral_centroid	gaussian_mixture_model_default	cosine_distance
12784	1.7917227164589622	melspectrogram	vector_quantization_default	cosine_distance
12792	1.5408171982792034	beat_synchronous_chroma_cens	vector_quantization	manhattan_distance
12793	1.5214075337448887	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
12794	1.9984692907834467	beat_synchronous_chroma_stft	gaussian_mixture_model_default	chebyshev_distance
12820	3.022842137621093	temporal_statistical_spectrum_descriptor	bypass	cosine_distance

Maria Panteli's melody dataset

class	iicsr	extractor	aggregator	distance
1	4.572860360301707	pitch_contour_segmentation	interval_abstraction	levenshtein_max
2	4.595488591478775	pitch_contour_segmentation	interval_abstraction	levenshtein_max
3	4.667953017999352	pitch_contour_segmentation	interval_abstraction	levenshtein_max
4	3.7801805173521292	pitch_contour_segmentation	interval_abstraction	levenshtein_max
5	4.253788622841754	pitch_contour_segmentation	interval_abstraction	levenshtein_max
6	3.0931585472915883	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
7	4.136376432826418	pitch_contour_segmentation	interval_abstraction	levenshtein_max
8	7.132299323200648	pitch_contour_segmentation	interval_abstraction	levenshtein_max
9	2.7462094457222794	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
10	3.301147886316078	pitch_contour_segmentation	markov_chain	circular_cosine
11	3.4250252510795147	pitch_contour_segmentation	interval_abstraction	levenshtein_max
12	2.8428993629829065	melspectrogram	statistical_summarization	cosine_distance
13	3.7872063093146475	pitch_contour_segmentation	interval_abstraction	lcs_max
14	2.9213992384749026	melspectrogram	statistical_summarization	cosine_distance
15	3.7533687103512112	pitch_contour_segmentation	interval_abstraction	lcs_max
16	4.9527143368654345	pitch_contour_segmentation	interval_abstraction	levenshtein_max
17	5.128621876014979	pitch_contour_segmentation	interval_abstraction	levenshtein_max
18	2.7718426025520984	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
19	2.30990245660279	melspectrogram	statistical_summarization	cosine_distance
20	2.9569345777365337	melspectrogram	statistical_summarization	cosine_distance
21	2.924364382427016	mfcc	vector_quantization	cosine_distance
22	4.455118828580867	spectral_contrast	vector_quantization	cosine_distance
23	3.43882193082738	melspectrogram	gaussian_mixture_model_default	cosine_distance
24	2.656617917998237	melspectrogram	gaussian_mixture_model_default	cosine_distance
25	2.9080653951108073	pitch_contour_segmentation	interval_abstraction	lcs_max
26	3.9429393369828185	melspectrogram	gaussian_mixture_model_default	cosine_distance
27	4.472476063911515	spectral_contrast	vector_quantization	manhattan_distance
28	4.241831353861312	melspectrogram	statistical_summarization	cosine_distance
29	4.742320714782647	spectral_contrast	vector_quantization	cosine_distance
30	3.236193595007395	melspectrogram	statistical_summarization	cosine_distance

Maria Panteli's rhythm dataset

class	iicsr	extractor	aggregator	distance
1	1.8670298087033916	beat_synchronous_chroma_cens	vector_quantization	manhattan_distance
2	2.2926001988195237	chroma_cens	vector_quantization	manhattan_distance
3	1.6188468257146416	chroma_cens	vector_quantization	cosine_distance
4	1.9375919403849882	chroma_cens	vector_quantization	cosine_distance
5	2.0600823372158277	chroma_cens	vector_quantization	cosine_distance
6	2.249490571880482	chroma_cens	vector_quantization	cosine_distance
7	2.4496064675664773	chroma_cens	vector_quantization	cosine_distance
8	1.8294307561901648	beat_synchronous_chroma_cens	vector_quantization	manhattan_distance
9	2.2143484693635	chroma_cens	vector_quantization	cosine_distance
10	3.2620774461342745	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
11	1.8691095336651231	chroma_cens	vector_quantization_default	manhattan_distance
12	1.8418994918528444	chroma_cens	vector_quantization_default	manhattan_distance
13	1.8522476160762056	chroma_cens	vector_quantization	cosine_distance
14	1.7902546240434094	chroma_cens	vector_quantization_default	manhattan_distance
15	1.8187801111781927	chroma_cens	vector_quantization	cosine_distance
16	1.9485394898754373	chroma_cens	vector_quantization	cosine_distance
17	1.7026595161486144	chroma_cens	vector_quantization	cosine_distance
18	2.314321102047266	chroma_cens	vector_quantization	cosine_distance
19	1.9083899662609827	beat_synchronous_chroma_stft	vector_quantization	manhattan_distance
20	1.7401751410973576	beat_synchronous_chroma_stft	vector_quantization	manhattan_distance
21	3.4049155987800286	chroma_cens	vector_quantization	manhattan_distance
22	3.4885142295054643	beat_synchronous_chroma_stft	vector_quantization	manhattan_distance
23	3.6681551328269824	beat_synchronous_chroma_stft	vector_quantization	manhattan_distance
24	4.164128240158876	chroma_cens	vector_quantization	manhattan_distance
25	4.463776112464625	chroma_cens	vector_quantization	manhattan_distance
26	3.4231621827272445	melspectrogram	vector_quantization	cosine_distance
27	4.647600957936456	beat_synchronous_chroma_cens	vector_quantization	cosine_distance
28	3.851326718857485	chroma_cens	vector_quantization	manhattan_distance
29	5.390396490175905	chroma_cens	vector_quantization	manhattan_distance
30	13.207691825597978	chroma_cens	vector_quantization	manhattan_distance

MAST

class	iicsr	extractor	aggregator	distance
51_rhy1	1.2710345335966193	mfcc	vector_quantization	cosine_distance
51_rhy2	1.197985004287646	mfcc	vector_quantization	cosine_distance
52_rhy1	1.2958063945996323	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
52_rhy2	1.3303252480126277	mfcc	vector_quantization	cosine_distance
53_rhy1	1.3105333145845612	melspectrogram	vector_quantization	cosine_distance
53_rhy2	1.365515475052475	melspectrogram	vector_quantization	cosine_distance
54_rhy1	1.2473952719687482	rhythm_histogram	bypass	manhattan_distance
54_rhy2	1.2915682840332523	mfcc	vector_quantization	cosine_distance
55_rhy1	1.324655702228605	mfcc	vector_quantization	cosine_distance
55_rhy2	1.157098644355708	mfcc	vector_quantization	cosine_distance
56_rhy1	1.4030468790783808	melspectrogram	vector_quantization	cosine_distance
56_rhy2	1.2637637104874466	mfcc	vector_quantization	cosine_distance
57_rhy1	1.4301647322521653	mfcc	vector_quantization	cosine_distance
57_rhy2	1.331310654157978	mfcc	vector_quantization	cosine_distance
58_rhy1	1.442056154281866	mfcc	vector_quantization	cosine_distance
58_rhy2	1.329289417750898	melspectrogram	vector_quantization	cosine_distance
59_rhy1	1.3757720348279594	mfcc	vector_quantization	cosine_distance
59_rhy2	1.4163457314191061	mfcc	vector_quantization	cosine_distance
61_rhy1	1.5787841569442553	mfcc	vector_quantization	cosine_distance
61_rhy2	1.5478398738313663	mfcc	vector_quantization	cosine_distance
62_rhy1	1.7420472205121904	mfcc	vector_quantization	cosine_distance
62_rhy2	1.8102568891528337	mfcc	vector_quantization	cosine_distance
63_rhy1	1.5051097622800966	mfcc	vector_quantization	cosine_distance
63_rhy2	1.5319079904177115	mfcc	vector_quantization	cosine_distance
64_rhy1	1.573149397178731	mfcc	vector_quantization	cosine_distance
64_rhy2	1.5771004756691684	mfcc	vector_quantization	cosine_distance
65_rhy1	1.7214771508170008	mfcc	vector_quantization	cosine_distance
65_rhy2	1.702037258445737	mfcc	vector_quantization	cosine_distance
66_rhy1	1.5756120013491706	mfcc	vector_quantization	cosine_distance
66_rhy2	1.7584688986199082	mfcc	vector_quantization	cosine_distance
67_rhy1	1.5631061272516145	mfcc	vector_quantization	cosine_distance
67_rhy2	1.7222187702130034	mfcc	vector_quantization	cosine_distance
68_rhy1	1.5207842589703118	mfcc	vector_quantization	cosine_distance
68_rhy2	1.404187410154036	mfcc	vector_quantization	cosine_distance
69_rhy1	1.7458435351239012	mfcc	vector_quantization	cosine_distance
69_rhy2	1.6958878785452038	mfcc	vector_quantization	cosine_distance
510_rhy1	1.3524313981519618	melspectrogram	vector_quantization	cosine_distance
510_rhy2	1.2268756183928735	chroma_cens	vector_quantization	cosine_distance
610_rhy1	1.952292573383342	mfcc	vector_quantization	cosine_distance
610_rhy2	1.8806557150616792	mfcc	vector_quantization	cosine_distance

1517-Artists

class	iicsr	extractor	aggregator	distance
alternative_and_punk	1.4999695490436216	melspectrogram	gaussian_mixture_model_default	cosine_distance
blues	1.1098871819330052	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
childrens	1.0943078219906563	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
classical	2.1164904537244684	mfcc	vector_quantization	cosine_distance
comedy_and_spoken_word	1.1974831893872648	melspectrogram	vector_quantization	manhattan_distance
country	1.2554695639407525	mfcc	vector_quantization	cosine_distance
easy_listening_and_vocals	1.1939354506841648	spectral_flatness	vector_quantization_default	manhattan_distance
electronic_and_dance	1.840397912731588	melspectrogram	gaussian_mixture_model_default	cosine_distance
folk	1.2152099198606334	temporal_statistical_spectrum_descriptor	bypass	cosine_distance

hip_hop	1.822437782260004	melspectrogram	gaussian_mixture_model_default	cosine_distance
jazz	1.2021325504515423	mfcc	vector_quantization	cosine_distance
latin	1.1231307443059342	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
new_age	1.251975624140489	temporal_statistical_spectrum_descriptor	bypass	cosine_distance
rb_and_soul	1.476072914544827	melspectrogram	gaussian_mixture_model_default	cosine_distance
reggae	1.542428608725201	melspectrogram	gaussian_mixture_model_default	cosine_distance
religious	1.0668655201385653	beat_synchronous_chroma_stft	vector_quantization	manhattan_distance
rock_and_pop	1.2498143324639641	melspectrogram	gaussian_mixture_model_default	cosine_distance
soundtracks_and_more	1.1794783186030748	rms	vector_quantization_default	cosine_distance
world	1.0778001669749437	pitch_contour_segmentation	interval_abstraction	lcs_min

MIR-QBSH

class	iicsr	extractor	aggregator	distance
00001	1.3426521013968042	beat_synchronous_chroma_cens	vector_quantization	cosine_distance
00002	1.1854384487609289	beat_synchronous_chroma_cqt	vector_quantization	cosine_distance
00003	1.2089379804091687	beat_synchronous_chroma_cqt	gaussian_mixture_model_default	chebyshev_distance
00004	1.5140063780774038	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00005	1.8185350445603963	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
00006	1.307848845538258	beat_synchronous_chroma_cqt	vector_quantization	cosine_distance
00007	1.4810408546023004	beat_synchronous_chroma_stft	vector_quantization	cosine_distance
00008	1.7058914361938693	beat_synchronous_chroma_cens	vector_quantization	cosine_distance
00009	1.2584274546232286	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00010	1.3240272737363754	pitch_contour_segmentation	interval_abstraction	levenshtein_max
00011	1.2868232903682821	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00012	1.235122897468527	pitch_contour_segmentation	interval_abstraction	levenshtein_max
00013	1.2408659176153771	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00014	1.3710733579205252	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00015	2.8752141436215215	pitch_contour_segmentation	interval_abstraction	levenshtein_max
00016	1.2416637016174383	beat_synchronous_chroma_stft	gaussian_mixture_model_default	chebyshev_distance
00017	1.2330353215917977	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00018	1.2735425266442444	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00019	1.3002635184876157	pitch_contour_segmentation	interval_abstraction	levenshtein_max
00020	1.3035672015047721	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00021	1.4207975124800925	pitch_contour_segmentation	interval_abstraction	levenshtein_max
00022	1.3482756484626444	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00023	1.3809539366454477	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00024	1.1404421313277269	rhythm_histogram	bypass	cosine_distance
00025	1.365174657637962	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00026	1.2129547851601532	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00027	1.2870527989905776	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00028	1.213312386482332	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00029	1.2694733437999601	pitch_contour_segmentation	interval_abstraction	levenshtein_max
00030	1.4310178987924125	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00031	1.2926576412946402	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00032	1.3987053026930807	pitch_contour_segmentation	interval_abstraction	levenshtein_max
00033	1.240558326933691	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00034	1.4092555463527239	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00035	1.3928981122158477	pitch_contour_segmentation	interval_abstraction	levenshtein_max
00036	1.2186706262622518	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00037	1.2591839456105867	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00038	1.4380810494107832	pitch_contour_segmentation	pitch_contour_5_levels	levenshtein_max
00039	1.295451309499923	pitch_contour_segmentation	pitch_contour_5_levels	levenshtein_max
00040	1.2838996250824963	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00041	1.26680104239057	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00042	1.3209991139147594	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00043	1.3880862217013903	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00044	1.1954010156115364	pitch_contour_segmentation	octave_abstraction	lcs_circular_min
00045	1.400643046993626	pitch_contour_segmentation	interval_abstraction	lcs_max
00046	1.46974416499097065	pitch_contour_segmentation	interval_abstraction	levenshtein_max
00047	1.3456196055598155	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
00048	1.385548715204191	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max

FMA-Small

class	iicsr	extractor	aggregator	distance
electronic	1.571253188813728	melspectrogram	gaussian_mixture_model_default	cosine_distance
experimental	1.079796885278995	chroma_cqt	gaussian_mixture_model_default	chebyshev_distance
folk	1.4259507088603285	mfcc	vector_quantization_default	cosine_distance
hiphop	1.7413277755764476	melspectrogram	gaussian_mixture_model_default	cosine_distance
instrumental	1.3366911248426074	spectral_flatness	vector_quantization_default	manhattan_distance
international	1.1580329180897504	spectral_rolloff	vector_quantization	cosine_distance
pop	1.1103872709568248	spectral_rolloff	vector_quantization_default	manhattan_distance
rock	1.2649471222355302	mfcc	vector_quantization_default	cosine_distance

Appendix B

Cover Song Identification: top-50 results per dataset

Covers80

line id	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
1	41.575	0.19359	31.0	0.19359	21.0	46.0	142.0	160.0
2	41.99375	0.19206	32.0	0.19206	20.0	44.0	142.0	160.0
3	42.3625	0.20598	27.5	0.20598	20.0	56.0	138.0	160.0
4	42.44375	0.1901	24.0	0.1901	18.0	57.0	141.0	160.0
5	42.4625	0.18129	32.0	0.18129	19.0	47.0	143.0	160.0
6	42.675	0.19459	24.0	0.19459	19.0	57.0	136.0	160.0
7	42.71875	0.17317	31.0	0.17317	18.0	46.0	142.0	160.0
8	43.01875	0.18078	34.0	0.18078	17.0	48.0	136.0	160.0
9	43.08125	0.20681	25.0	0.20681	23.0	48.0	137.0	160.0
10	43.35625	0.16701	29.5	0.16701	16.0	46.0	137.0	160.0
11	43.35625	0.16701	29.5	0.16701	16.0	46.0	137.0	160.0
12	43.35625	0.16701	29.5	0.16701	16.0	46.0	137.0	160.0
13	43.45	0.1628	29.5	0.1628	15.0	44.0	137.0	160.0
14	43.925	0.1763	36.0	0.1763	17.0	45.0	138.0	160.0
15	44.5	0.17416	36.0	0.17416	17.0	45.0	137.0	160.0
16	44.53125	0.17385	36.0	0.17385	17.0	45.0	137.0	160.0
17	44.78125	0.22168	33.0	0.22168	26.0	51.0	136.0	160.0
18	44.80625	0.20759	34.5	0.20759	23.0	53.0	139.0	160.0
19	45.0	0.20318	29.0	0.20318	22.0	53.0	137.0	160.0
20	45.0125	0.17628	35.0	0.17628	20.0	45.0	134.0	160.0
21	45.0625	0.17673	32.5	0.17673	17.0	53.0	140.0	160.0
22	45.0625	0.17687	31.5	0.17687	17.0	53.0	139.0	160.0
23	45.15	0.16971	38.5	0.16971	17.0	45.0	136.0	160.0
24	45.15	0.20324	31.5	0.20324	22.0	52.0	137.0	160.0
25	45.15625	0.1726	37.0	0.1726	17.0	45.0	138.0	160.0
26	45.2875	0.2088	27.0	0.2088	23.0	50.0	135.0	160.0
27	45.36875	0.24177	26.5	0.24177	29.0	56.0	135.0	160.0
28	45.38125	0.21505	27.0	0.21505	23.0	57.0	133.0	160.0
29	45.4625	0.17864	33.0	0.17864	20.0	42.0	137.0	160.0
30	45.61875	0.20712	25.5	0.20712	20.0	57.0	128.0	160.0
31	45.83125	0.22481	30.0	0.22481	26.0	51.0	134.0	160.0
32	46.04375	0.19432	29.5	0.19432	20.0	50.0	132.0	160.0
33	46.06875	0.1945	29.5	0.1945	20.0	50.0	132.0	160.0
34	46.09375	0.17987	31.0	0.17987	19.0	46.0	135.0	160.0
35	46.16875	0.16105	31.5	0.16105	13.0	50.0	136.0	160.0
36	46.19375	0.21467	29.5	0.21467	23.0	49.0	134.0	160.0
37	46.2	0.21456	29.5	0.21456	23.0	49.0	134.0	160.0
38	46.21875	0.21466	29.5	0.21466	23.0	49.0	134.0	160.0
39	46.2375	0.21455	29.5	0.21455	23.0	49.0	134.0	160.0
40	46.25625	0.2138	28.0	0.2138	24.0	53.0	134.0	160.0
41	46.2625	0.20077	32.0	0.20077	20.0	51.0	136.0	160.0
42	46.3375	0.21427	29.5	0.21427	24.0	53.0	133.0	160.0
43	46.41875	0.20396	29.0	0.20396	21.0	49.0	140.0	160.0
44	46.48125	0.1864	31.0	0.1864	20.0	47.0	134.0	160.0
45	46.48125	0.21301	30.0	0.21301	22.0	53.0	136.0	160.0
46	46.55	0.2003	29.0	0.2003	20.0	49.0	140.0	160.0
47	46.6125	0.21394	33.0	0.21394	21.0	57.0	137.0	160.0
48	46.7375	0.20593	26.5	0.20593	22.0	51.0	129.0	160.0
49	46.76875	0.21671	29.5	0.21671	24.0	50.0	135.0	160.0
50	46.8	0.18481	29.5	0.18481	18.0	46.0	130.0	160.0

line id	extractor	aggregator	distance
1	chroma_stft	diff_stats_1	cosine_distance_oti
2	chroma_stft	basic_stats_1	cosine_distance_oti
3	beat_synchronous_chroma_cens	basic_stats_2	manhattan_distance_oti
4	beat_synchronous_chroma_cens	basic_stats_2	euclidean_distance_oti
5	chroma_stft	diff_stats_1	manhattan_distance_oti
6	beat_synchronous_chroma_cens	basic_stats_2	cosine_distance_oti
7	chroma_stft	statistical_summarization	manhattan_distance_oti
8	chroma_stft	diff_stats_1	euclidean_distance_oti
9	chroma_stft	statistical_summarization	cosine_distance_oti
10	chroma_stft	basic_stats_2	chebyshev_distance_oti
11	chroma_stft	basic_stats_1	chebyshev_distance_oti
12	chroma_stft	diff_stats_1	chebyshev_distance_oti

13	chroma_stft	statistical_summarization	chebyshev_distance_oti
14	chroma_stft	basic_stats_2	cosine_distance_oti
15	chroma_stft	basic_stats_1	euclidean_distance_oti
16	chroma_stft	basic_stats_2	euclidean_distance_oti
17	beat_synchronous_chroma_cqt	diff_stats_1	cosine_distance_oti
18	beat_synchronous_chroma_cqt	basic_stats_1	cosine_distance_oti
19	beat_synchronous_chroma_cens	diff_stats_1	cosine_distance_oti
20	chroma_stft	statistical_summarization	euclidean_distance_oti
21	beat_synchronous_chroma_cens	basic_stats_1	cosine_distance_oti
22	beat_synchronous_chroma_cens	basic_stats_1	euclidean_distance_oti
23	chroma_stft	basic_stats_2	manhattan_distance_oti
24	beat_synchronous_chroma_cens	diff_stats_1	euclidean_distance_oti
25	chroma_stft	basic_stats_1	manhattan_distance_oti
26	beat_synchronous_chroma_cens	basic_stats_2	manhattan_distance_oti
27	beat_synchronous_chroma_cqt	diff_stats_1	manhattan_distance_oti
28	beat_synchronous_chroma_cqt	diff_stats_2	manhattan_distance_oti
29	chroma_stft	diff_stats_1	manhattan_distance
30	beat_synchronous_chroma_cens	diff_stats_2	cosine_distance_oti
31	beat_synchronous_chroma_cqt	basic_stats_2	manhattan_distance_oti
32	beat_synchronous_chroma_cens	basic_stats_1	cosine_distance
33	beat_synchronous_chroma_cens	basic_stats_1	euclidean_distance
34	chroma_cqt	diff_stats_1	manhattan_distance
35	beat_synchronous_chroma_cens	basic_stats_1	manhattan_distance_oti
36	chroma_cens	diff_stats_1	cosine_distance
37	chroma_cens	diff_stats_1	euclidean_distance
38	chroma_cens	basic_stats_1	cosine_distance
39	chroma_cens	basic_stats_1	euclidean_distance
40	beat_synchronous_chroma_cens	diff_stats_1	cosine_distance
41	beat_synchronous_chroma_cens	diff_stats_1	manhattan_distance_oti
42	beat_synchronous_chroma_cens	diff_stats_1	euclidean_distance
43	chroma_cens	diff_stats_1	manhattan_distance
44	chroma_cqt	diff_stats_1	euclidean_distance
45	beat_synchronous_chroma_cqt	diff_stats_1	euclidean_distance_oti
46	chroma_cens	basic_stats_1	manhattan_distance
47	beat_synchronous_chroma_cens	diff_stats_2	manhattan_distance_oti
48	chroma_cqt	vector_quantization_default	cosine_distance
49	beat_synchronous_chroma_cqt	basic_stats_2	euclidean_distance_oti
50	chroma_cqt	statistical_summarization	euclidean_distance

YouTubeCovers

line id	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
1	7.97143	0.6942	1.0	0.36114	219.0	296.0	345.0	350.0
2	9.41143	0.63231	1.0	0.29777	189.0	279.0	345.0	350.0
3	14.1	0.4344	3.5	0.19221	110.0	231.0	343.0	350.0
4	14.13714	0.40846	5.0	0.1805	103.0	233.0	344.0	350.0
5	14.71143	0.38021	5.0	0.15415	85.0	227.0	344.0	350.0
6	15.89429	0.37811	5.0	0.15807	93.0	216.0	346.0	350.0
7	15.89429	0.37811	5.0	0.15807	93.0	216.0	346.0	350.0
8	16.46286	0.37605	5.5	0.15219	86.0	223.0	343.0	350.0
9	16.85429	0.5271	2.0	0.21466	153.0	247.0	335.0	350.0
10	17.06	0.35579	6.0	0.14139	78.0	225.0	342.0	350.0
11	17.96	0.5303	2.0	0.21618	154.0	252.0	332.0	350.0
12	18.41429	0.37785	6.0	0.15339	93.0	210.0	341.0	350.0
13	18.8	0.38707	5.0	0.15379	95.0	213.0	338.0	350.0
14	18.82857	0.36226	5.0	0.14261	81.0	219.0	337.0	350.0
15	19.38571	0.38507	5.0	0.15785	93.0	218.0	339.0	350.0
16	19.45143	0.37268	6.0	0.14618	90.0	218.0	336.0	350.0
17	19.46857	0.36426	5.0	0.14654	84.0	215.0	336.0	350.0
18	19.54571	0.39092	6.0	0.15383	100.0	205.0	340.0	350.0
19	19.56	0.33607	8.0	0.12278	76.0	196.0	339.0	350.0
20	19.61143	0.3506	7.0	0.13665	86.0	197.0	339.0	350.0
21	19.63143	0.42627	4.0	0.1657	109.0	230.0	335.0	350.0
22	19.76	0.40204	4.5	0.1571	101.0	221.0	333.0	350.0
23	19.79429	0.35146	7.0	0.13543	80.0	214.0	338.0	350.0
24	19.83143	0.37327	5.0	0.14771	87.0	213.0	338.0	350.0
25	19.88857	0.37544	5.0	0.14857	88.0	214.0	338.0	350.0
26	19.90857	0.38234	6.0	0.14595	93.0	218.0	336.0	350.0
27	19.92286	0.35465	6.0	0.13542	84.0	210.0	335.0	350.0
28	20.16571	0.35024	7.0	0.13404	80.0	209.0	337.0	350.0
29	20.18	0.42428	5.0	0.16905	113.0	228.0	335.0	350.0
30	20.20286	0.35045	7.0	0.13408	80.0	210.0	337.0	350.0
31	20.21429	0.38504	7.0	0.14998	101.0	207.0	335.0	350.0
32	20.32286	0.38765	6.5	0.15122	102.0	210.0	336.0	350.0
33	20.36571	0.33463	7.0	0.12613	77.0	204.0	336.0	350.0
34	20.48	0.3748	5.5	0.14459	92.0	211.0	337.0	350.0
35	20.48571	0.33411	8.0	0.12859	78.0	194.0	340.0	350.0
36	20.58571	0.3173	7.0	0.12465	71.0	200.0	339.0	350.0
37	20.61429	0.36799	5.0	0.13742	85.0	224.0	331.0	350.0
38	20.72286	0.33957	6.0	0.1267	74.0	204.0	336.0	350.0
39	20.86571	0.35297	6.0	0.13521	82.0	208.0	340.0	350.0
40	20.94857	0.39652	6.0	0.15371	101.0	215.0	333.0	350.0
41	21.01143	0.34911	6.0	0.13439	79.0	207.0	339.0	350.0
42	21.16571	0.38376	6.0	0.14662	97.0	207.0	331.0	350.0
43	21.16571	0.36152	6.0	0.13785	87.0	210.0	335.0	350.0
44	21.44286	0.33155	9.0	0.12398	78.0	193.0	340.0	350.0
45	21.44857	0.3592	6.0	0.13646	87.0	209.0	331.0	350.0
46	21.54286	0.33319	9.0	0.12406	79.0	194.0	340.0	350.0
47	21.58571	0.36208	6.0	0.13483	88.0	210.0	336.0	350.0
48	21.72286	0.38764	7.0	0.15387	101.0	204.0	328.0	350.0
49	21.84571	0.36061	6.0	0.14888	92.0	200.0	334.0	350.0
50	21.92	0.31323	7.5	0.11445	69.0	193.0	340.0	350.0

line id	extractor	aggregator	distance
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1	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean
2	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
3	pitch_contour_segmentation	markov_chain	circular_manhattan
4	pitch_contour_segmentation	markov_chain	circular_cosine
5	chroma_stft	statistical_summarization	cosine_distance_oti
6	pitch_contour_segmentation	markov_chain	circular_euclidean
7	pitch_contour_segmentation	markov_chain	circular_chebyshev
8	chroma_stft	diff_stats_1	cosine_distance_oti
9	pitch_contour_segmentation	octave_abstraction	lcs_circular_max
10	chroma_stft	basic_stats_1	cosine_distance_oti
11	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_mean
12	beat_synchronous_chroma_cens	basic_stats_2	euclidean_distance_oti
13	beat_synchronous_chroma_cens	basic_stats_2	manhattan_distance_oti
14	chroma_cens	basic_stats_2	euclidean_distance_oti
15	beat_synchronous_chroma_cens	basic_stats_2	cosine_distance_oti
16	chroma_stft	diff_stats_1	euclidean_distance_oti
17	chroma_cens	basic_stats_2	cosine_distance_oti
18	beat_synchronous_chroma_cqt	diff_stats_1	cosine_distance_oti
19	beat_synchronous_chroma_stft	statistical_summarization	cosine_distance_oti
20	beat_synchronous_chroma_cqt	statistical_summarization	cosine_distance_oti
21	beat_synchronous_chroma_cens	diff_stats_2	manhattan_distance_oti
22	beat_synchronous_chroma_cens	diff_stats_2	euclidean_distance_oti
23	chroma_stft	basic_stats_2	cosine_distance_oti
24	chroma_stft	statistical_summarization	manhattan_distance_oti
25	chroma_stft	diff_stats_1	manhattan_distance_oti
26	chroma_cens	basic_stats_2	manhattan_distance_oti
27	chroma_cens	statistical_summarization	manhattan_distance_oti
28	chroma_stft	basic_stats_1	euclidean_distance_oti
29	beat_synchronous_chroma_cens	diff_stats_2	cosine_distance_oti
30	chroma_stft	basic_stats_2	euclidean_distance_oti
31	beat_synchronous_chroma_cens	diff_stats_1	cosine_distance_oti
32	beat_synchronous_chroma_cens	diff_stats_1	euclidean_distance_oti
33	chroma_cqt	statistical_summarization	cosine_distance_oti
34	beat_synchronous_chroma_cens	statistical_summarization	manhattan_distance_oti
35	beat_synchronous_chroma_cqt	basic_stats_1	cosine_distance_oti
36	beat_synchronous_chroma_stft	diff_stats_2	manhattan_distance_oti
37	beat_synchronous_chroma_cqt	statistical_summarization	manhattan_distance_oti
38	chroma_cqt	statistical_summarization	manhattan_distance_oti
39	chroma_stft	basic_stats_1	manhattan_distance_oti
40	beat_synchronous_chroma_cqt	diff_stats_1	manhattan_distance_oti
41	chroma_stft	basic_stats_2	manhattan_distance_oti
42	beat_synchronous_chroma_cqt	diff_stats_1	euclidean_distance_oti
43	chroma_stft	statistical_summarization	euclidean_distance_oti
44	beat_synchronous_chroma_cens	basic_stats_1	euclidean_distance_oti
45	beat_synchronous_chroma_stft	diff_stats_1	cosine_distance_oti
46	beat_synchronous_chroma_cens	basic_stats_1	cosine_distance_oti
47	beat_synchronous_chroma_stft	diff_stats_1	manhattan_distance_oti
48	beat_synchronous_chroma_cens	diff_stats_1	manhattan_distance_oti
49	beat_synchronous_chroma_cqt	diff_stats_2	manhattan_distance_oti
50	chroma_stft	diff_stats_1	chebyshev_distance_oti

Covers1000

line id	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
1	144.041	0.25731	35.0	0.19159	201.0	366.0	636.0	1000.0
2	175.546	0.09845	74.5	0.06977	52.0	188.0	548.0	1000.0
3	180.808	0.13566	75.0	0.09752	77.0	249.0	551.0	1000.0
4	181.48	0.15934	72.0	0.11552	103.0	261.0	558.0	1000.0
5	183.802	0.0861	95.0	0.06054	48.0	155.0	515.0	1000.0
6	184.645	0.12143	81.0	0.08497	70.0	213.0	533.0	1000.0
7	185.462	0.13359	79.0	0.09661	80.0	236.0	540.0	1000.0
8	185.521	0.14401	84.5	0.10473	93.0	228.0	525.0	1000.0
9	185.781	0.09549	97.0	0.06776	49.0	183.0	512.0	1000.0
10	185.884	0.14356	86.0	0.10421	93.0	229.0	526.0	1000.0
11	186.181	0.13101	79.5	0.09636	73.0	233.0	541.0	1000.0
12	187.932	0.1348	72.0	0.09188	86.0	224.0	558.0	1000.0
13	188.264	0.13732	86.0	0.10134	84.0	231.0	527.0	1000.0
14	188.475	0.14861	87.0	0.10949	100.0	234.0	522.0	1000.0
15	189.284	0.1337	84.5	0.09952	81.0	235.0	530.0	1000.0
16	189.312	0.11524	84.0	0.08645	67.0	197.0	532.0	1000.0
17	189.973	0.10335	84.5	0.07515	59.0	179.0	538.0	1000.0
18	190.38	0.09767	96.0	0.06738	54.0	177.0	510.0	1000.0
19	190.65	0.11334	94.0	0.08278	64.0	195.0	521.0	1000.0
20	190.742	0.12131	87.0	0.09107	72.0	207.0	531.0	1000.0
21	190.766	0.13448	87.0	0.09512	88.0	213.0	533.0	1000.0
22	190.953	0.13206	86.0	0.09652	87.0	221.0	529.0	1000.0
23	191.334	0.10765	90.0	0.07774	62.0	185.0	516.0	1000.0
24	191.445	0.10792	90.0	0.07784	63.0	185.0	518.0	1000.0
25	191.543	0.1073	91.5	0.07762	63.0	185.0	514.0	1000.0
26	191.648	0.1072	91.5	0.07753	63.0	185.0	515.0	1000.0
27	191.84	0.11782	96.0	0.08641	72.0	194.0	510.0	1000.0
28	191.898	0.11821	95.0	0.08651	73.0	195.0	508.0	1000.0
29	192.048	0.10912	82.0	0.07906	61.0	198.0	529.0	1000.0
30	192.494	0.10853	96.5	0.07907	59.0	185.0	514.0	1000.0
31	192.662	0.11786	90.0	0.08843	65.0	212.0	526.0	1000.0
32	192.749	0.11648	98.5	0.08777	74.0	197.0	503.0	1000.0
33	193.164	0.10728	97.5	0.07317	61.0	193.0	508.0	1000.0
34	193.857	0.09469	91.0	0.06679	45.0	185.0	523.0	1000.0
35	194.399	0.12253	80.0	0.09197	73.0	217.0	533.0	1000.0
36	195.464	0.11381	93.5	0.08471	65.0	204.0	511.0	1000.0
37	195.724	0.10344	90.0	0.0741	55.0	195.0	527.0	1000.0
38	195.92	0.1074	93.0	0.0776	62.0	190.0	512.0	1000.0
39	196.486	0.18707	81.0	0.13042	138.0	275.0	534.0	1000.0
40	196.723	0.10651	91.5	0.07646	57.0	188.0	519.0	1000.0
41	197.11	0.10332	95.5	0.07532	55.0	189.0	506.0	1000.0
42	198.292	0.13356	91.0	0.10005	80.0	237.0	517.0	1000.0

43	198.426	0.10194	103.5	0.07181	53.0	193.0	497.0	1000.0
44	199.148	0.11907	87.0	0.08307	73.0	207.0	521.0	1000.0
45	199.706	0.07955	104.0	0.05329	43.0	144.0	495.0	1000.0
46	199.788	0.103	99.0	0.07324	57.0	191.0	504.0	1000.0
47	200.046	0.07752	108.0	0.05253	36.0	147.0	484.0	1000.0
48	200.077	0.11595	88.5	0.0858	61.0	217.0	520.0	1000.0
49	200.237	0.11163	103.0	0.07722	64.0	196.0	494.0	1000.0
50	200.555	0.06977	119.0	0.04798	35.0	122.0	465.0	1000.0

line id	extractor	aggregator	distance
1	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean
2	beat_synchronous_chroma_stft	diff_stats_1	cosine_distance_oti
3	beat_synchronous_chroma_cqt	diff_stats_1	manhattan_distance_oti
4	rhythm_histogram	bypass	cosine_distance
5	beat_synchronous_chroma_stft	basic_stats_1	cosine_distance_oti
6	chroma_cens	basic_stats_2	manhattan_distance_oti
7	beat_synchronous_chroma_cqt	diff_stats_1	euclidean_distance_oti
8	beat_synchronous_chroma_cens	diff_stats_1	cosine_distance_oti
9	beat_synchronous_chroma_stft	diff_stats_1	manhattan_distance_oti
10	beat_synchronous_chroma_cens	diff_stats_1	euclidean_distance_oti
11	beat_synchronous_chroma_cqt	diff_stats_1	cosine_distance_oti
12	chroma_cqt	statistical_summarization	manhattan_distance_oti
13	beat_synchronous_chroma_cens	basic_stats_2	manhattan_distance_oti
14	beat_synchronous_chroma_cens	diff_stats_1	manhattan_distance_oti
15	beat_synchronous_chroma_cqt	statistical_summarization	manhattan_distance_oti
16	beat_synchronous_chroma_cqt	basic_stats_1	cosine_distance_oti
17	beat_synchronous_chroma_stft	statistical_summarization	cosine_distance_oti
18	beat_synchronous_chroma_stft	diff_stats_1	euclidean_distance_oti
19	chroma_cens	diff_stats_1	manhattan_distance_oti
20	beat_synchronous_chroma_cens	basic_stats_2	euclidean_distance_oti
21	chroma_cens	statistical_summarization	manhattan_distance_oti
22	beat_synchronous_chroma_cens	statistical_summarization	manhattan_distance_oti
23	chroma_cens	diff_stats_1	euclidean_distance_oti
24	chroma_cens	basic_stats_1	euclidean_distance_oti
25	chroma_cens	diff_stats_1	cosine_distance_oti
26	chroma_cens	basic_stats_1	cosine_distance_oti
27	beat_synchronous_chroma_cens	basic_stats_1	euclidean_distance_oti
28	beat_synchronous_chroma_cens	basic_stats_1	cosine_distance_oti
29	chroma_cqt	diff_stats_1	cosine_distance_oti
30	chroma_cens	basic_stats_1	manhattan_distance_oti
31	beat_synchronous_chroma_cqt	basic_stats_1	manhattan_distance_oti
32	beat_synchronous_chroma_cens	basic_stats_1	manhattan_distance_oti
33	chroma_cens	basic_stats_2	euclidean_distance_oti
34	chroma_stft	statistical_summarization	cosine_distance_oti
35	beat_synchronous_chroma_cens	basic_stats_2	cosine_distance_oti
36	beat_synchronous_chroma_cqt	basic_stats_1	euclidean_distance_oti
37	chroma_cqt	basic_stats_1	cosine_distance_oti
38	chroma_cqt	diff_stats_1	manhattan_distance_oti
39	pitch_contour_segmentation	octave_abstraction	lcs_circular_max
40	chroma_cqt	basic_stats_1	manhattan_distance_oti
41	chroma_cqt	diff_stats_1	euclidean_distance_oti
42	beat_synchronous_chroma_cens	diff_stats_2	manhattan_distance_oti
43	beat_synchronous_chroma_stft	statistical_summarization	manhattan_distance_oti
44	chroma_cqt	statistical_summarization	cosine_distance_oti
45	beat_synchronous_chroma_stft	diff_stats_2	manhattan_distance_oti
46	chroma_cqt	basic_stats_1	euclidean_distance_oti
47	beat_synchronous_chroma_stft	basic_stats_2	euclidean_distance_oti
48	beat_synchronous_chroma_cens	diff_stats_2	cosine_distance_oti
49	chroma_cqt	statistical_summarization	euclidean_distance_oti
50	beat_synchronous_chroma_stft	diff_stats_1	chebyshev_distance_oti

Mazurkas

line id	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
1	4.15724	0.95774	1.0	0.82286	2561.0	2714.0	2728.0	2739.0
2	4.46479	0.87347	1.0	0.33623	2251.0	2638.0	2722.0	2740.0
3	4.6297	0.83039	1.0	0.28564	2076.0	2620.0	2721.0	2740.0
4	4.65268	0.85999	1.0	0.32391	2197.0	2622.0	2717.0	2741.0
5	4.86173	0.8785	1.0	0.3994	2241.0	2671.0	2718.0	2741.0
6	4.86647	0.83115	1.0	0.30325	2067.0	2615.0	2723.0	2739.0
7	4.95659	0.81238	1.0	0.24961	2018.0	2583.0	2722.0	2740.0
8	4.9865	0.80264	1.0	0.2673	1965.0	2593.0	2726.0	2741.0
9	5.08063	0.95648	1.0	0.86734	2551.0	2713.0	2728.0	2737.0
10	5.14447	0.79237	1.0	0.30303	1921.0	2602.0	2722.0	2741.0
11	5.23896	0.75554	1.0	0.26523	1787.0	2572.0	2722.0	2741.0
12	5.24298	0.75791	1.0	0.26433	1795.0	2574.0	2722.0	2740.0
13	5.25939	0.80314	1.0	0.30854	1964.0	2605.0	2722.0	2740.0
14	5.29734	0.83466	1.0	0.3252	2087.0	2614.0	2720.0	2739.0
15	5.3185	0.89443	1.0	0.47089	2314.0	2676.0	2717.0	2740.0
16	5.32908	0.83066	1.0	0.31932	2066.0	2630.0	2714.0	2741.0
17	5.3371	0.78583	1.0	0.29183	1898.0	2603.0	2725.0	2740.0
18	5.37468	0.76307	1.0	0.2816	1815.0	2577.0	2719.0	2741.0
19	5.4097	0.81851	1.0	0.29689	2033.0	2590.0	2714.0	2741.0
20	5.42868	0.76486	1.0	0.25983	1823.0	2564.0	2721.0	2740.0
21	5.44655	0.85087	1.0	0.35608	2147.0	2635.0	2714.0	2741.0
22	5.44874	0.76409	1.0	0.26173	1803.0	2593.0	2722.0	2739.0
23	5.4513	0.75756	1.0	0.27149	1795.0	2579.0	2723.0	2740.0
24	5.45275	0.78294	1.0	0.25122	1902.0	2563.0	2724.0	2741.0
25	5.4564	0.84368	1.0	0.38897	2099.0	2643.0	2714.0	2741.0
26	5.45677	0.81909	1.0	0.27946	2034.0	2592.0	2716.0	2740.0
27	5.46333	0.75744	1.0	0.2692	1797.0	2578.0	2723.0	2740.0
28	5.46771	0.75683	1.0	0.27046	1795.0	2579.0	2723.0	2740.0
29	5.49945	0.8628	1.0	0.37915	2192.0	2651.0	2716.0	2741.0
30	5.50967	0.80716	1.0	0.31016	1997.0	2595.0	2718.0	2739.0
31	5.52171	0.81355	1.0	0.28902	2018.0	2592.0	2716.0	2740.0

32	5.56841	0.79819	1.0	0.29974	1938.0	2611.0	2713.0	2741.0
33	5.6421	0.77203	1.0	0.26002	1852.0	2563.0	2720.0	2739.0
34	5.64757	0.76215	1.0	0.24718	1815.0	2566.0	2715.0	2739.0
35	5.75593	0.80746	1.0	0.25716	2016.0	2558.0	2711.0	2741.0
36	5.7822	0.88595	1.0	0.45548	2277.0	2676.0	2715.0	2739.0
37	5.79022	0.95151	1.0	0.79202	2535.0	2703.0	2726.0	2735.0
38	5.79168	0.68573	1.0	0.18034	1530.0	2526.0	2719.0	2741.0
39	5.79387	0.84458	1.0	0.38471	2113.0	2641.0	2714.0	2741.0
40	5.80482	0.88397	1.0	0.44858	2269.0	2669.0	2713.0	2741.0
41	5.87888	0.84451	1.0	0.38817	2122.0	2643.0	2714.0	2741.0
42	5.88034	0.79773	1.0	0.30175	1942.0	2598.0	2721.0	2739.0
43	5.92886	0.85721	1.0	0.39831	2171.0	2648.0	2714.0	2740.0
44	5.93506	0.92876	1.0	0.59167	2458.0	2685.0	2716.0	2739.0
45	5.94163	0.84747	1.0	0.39376	2126.0	2639.0	2715.0	2741.0
46	6.02007	0.80473	1.0	0.26676	1990.0	2563.0	2712.0	2740.0
47	6.03101	0.75188	1.0	0.27081	1788.0	2581.0	2715.0	2741.0
48	6.06421	0.80356	1.0	0.26642	1986.0	2563.0	2711.0	2740.0
49	6.06567	0.84628	1.0	0.37895	2132.0	2636.0	2715.0	2741.0
50	6.07224	0.86948	1.0	0.39357	2212.0	2658.0	2712.0	2740.0

line id	extractor	aggregator	distance
1	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
2	beat_synchronous_chroma_cqt	statistical_summarization	manhattan_distance_oti
3	chroma_cqt	statistical_summarization	manhattan_distance_oti
4	beat_synchronous_chroma_cens	statistical_summarization	manhattan_distance_oti
5	beat_synchronous_chroma_stft	statistical_summarization	manhattan_distance_oti
6	beat_synchronous_chroma_cens	diff_stats_2	manhattan_distance_oti
7	chroma_stft	statistical_summarization	manhattan_distance_oti
8	chroma_stft	statistical_summarization	cosine_distance_oti
9	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean
10	chroma_stft	diff_stats_1	cosine_distance_oti
11	chroma_stft	basic_stats_1	manhattan_distance_oti
12	chroma_stft	basic_stats_2	manhattan_distance_oti
13	chroma_stft	diff_stats_1	manhattan_distance_oti
14	beat_synchronous_chroma_cqt	diff_stats_1	manhattan_distance_oti
15	beat_synchronous_chroma_stft	diff_stats_1	manhattan_distance_oti
16	beat_synchronous_chroma_stft	diff_stats_1	chebyshev_distance_oti
17	chroma_stft	diff_stats_1	euclidean_distance_oti
18	chroma_stft	basic_stats_1	cosine_distance_oti
19	beat_synchronous_chroma_cqt	diff_stats_1	cosine_distance_oti
20	beat_synchronous_chroma_cens	diff_stats_2	cosine_distance_oti
21	beat_synchronous_chroma_stft	statistical_summarization	euclidean_distance_oti
22	chroma_stft	diff_stats_2	manhattan_distance_oti
23	chroma_stft	basic_stats_2	cosine_distance_oti
24	chroma_stft	statistical_summarization	euclidean_distance_oti
25	beat_synchronous_chroma_stft	basic_stats_1	manhattan_distance_oti
26	beat_synchronous_chroma_cens	diff_stats_1	manhattan_distance_oti
27	chroma_stft	basic_stats_2	euclidean_distance_oti
28	chroma_stft	basic_stats_1	euclidean_distance_oti
29	beat_synchronous_chroma_stft	statistical_summarization	cosine_distance_oti
30	beat_synchronous_chroma_cens	basic_stats_2	manhattan_distance_oti
31	beat_synchronous_chroma_cqt	diff_stats_1	euclidean_distance_oti
32	beat_synchronous_chroma_stft	basic_stats_1	chebyshev_distance_oti
33	beat_synchronous_chroma_cens	diff_stats_2	euclidean_distance_oti
34	chroma_cqt	diff_stats_1	manhattan_distance_oti
35	beat_synchronous_chroma_cqt	statistical_summarization	cosine_distance_oti
36	beat_synchronous_chroma_stft	diff_stats_1	cosine_distance_oti
37	pitch_contour_segmentation	octave_abstraction	lcs_circular_max
38	tonnetz	diff_stats_2	manhattan_distance
39	beat_synchronous_chroma_stft	basic_stats_1	euclidean_distance_oti
40	beat_synchronous_chroma_stft	diff_stats_1	euclidean_distance_oti
41	beat_synchronous_chroma_stft	basic_stats_2	euclidean_distance_oti
42	beat_synchronous_chroma_cqt	diff_stats_2	manhattan_distance_oti
43	beat_synchronous_chroma_stft	basic_stats_2	manhattan_distance_oti
44	beat_synchronous_chroma_cens	statistical_summarization	manhattan_distance
45	beat_synchronous_chroma_stft	basic_stats_1	cosine_distance_oti
46	beat_synchronous_chroma_cens	diff_stats_1	cosine_distance_oti
47	beat_synchronous_chroma_stft	statistical_summarization	chebyshev_distance_oti
48	beat_synchronous_chroma_cens	diff_stats_1	euclidean_distance_oti
49	beat_synchronous_chroma_stft	basic_stats_2	cosine_distance_oti
50	beat_synchronous_chroma_stft	diff_stats_1	chebyshev_distance

SHS9K

line id	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
1	47.57883	0.40387	6.0	0.05102	3008.0	5188.0	8067.0	9265.0
2	56.67866	0.33549	11.0	0.03429	2385.0	4527.0	7741.0	9273.0
3	59.06128	0.31115	13.0	0.02701	2182.0	4334.0	7658.0	9272.0
4	62.9398	0.23255	15.0	0.02777	1275.0	3990.0	7836.0	9240.0
5	63.73713	0.22736	16.0	0.02813	1234.0	3914.0	7809.0	9238.0
6	64.75038	0.22813	16.0	0.02696	1265.0	3888.0	7787.0	9237.0
7	65.22755	0.22587	16.0	0.02669	1222.0	3899.0	7766.0	9236.0
8	65.88273	0.18724	20.0	0.02269	927.0	3407.0	7716.0	9243.0
9	66.06203	0.29483	16.0	0.02617	2038.0	4100.0	7485.0	9270.0
10	66.90114	0.18625	20.0	0.02065	903.0	3429.0	7646.0	9252.0
11	67.6457	0.20722	18.0	0.02519	1073.0	3676.0	7713.0	9234.0
12	68.04534	0.20876	18.0	0.02622	1107.0	3640.0	7739.0	9235.0
13	68.12858	0.21972	18.0	0.0274	1199.0	3768.0	7697.0	9229.0
14	68.27838	0.18492	21.0	0.02028	906.0	3393.0	7621.0	9251.0
15	68.3067	0.18812	22.0	0.0214	953.0	3321.0	7576.0	9251.0
16	68.89296	0.21759	18.0	0.02539	1200.0	3719.0	7666.0	9245.0
17	69.16412	0.18338	20.0	0.02168	874.0	3397.0	7628.0	9249.0
18	69.28484	0.2129	18.0	0.02628	1147.0	3730.0	7667.0	9238.0
19	69.45402	0.15611	25.0	0.02011	698.0	2982.0	7538.0	9259.0
20	69.52305	0.21339	19.0	0.02691	1162.0	3616.0	7615.0	9247.0

21	69.53328	0.18706	21.0	0.01899	948.0	3317.0	7562.0	9256.0
22	69.66078	0.19729	20.0	0.02591	1026.0	3507.0	7668.0	9231.0
23	69.76125	0.17147	23.0	0.02174	837.0	3097.0	7556.0	9248.0
24	69.93129	0.19109	20.0	0.02507	970.0	3431.0	7672.0	9230.0
25	70.12966	0.17313	23.0	0.02266	851.0	3149.0	7559.0	9246.0
26	70.39436	0.20682	18.0	0.02627	1072.0	3685.0	7658.0	9221.0
27	70.79098	0.19835	20.0	0.02294	998.0	3558.0	7648.0	9234.0
28	70.81542	0.15369	26.0	0.01974	699.0	2908.0	7439.0	9259.0
29	70.87476	0.21268	19.0	0.02572	1144.0	3618.0	7610.0	9226.0
30	70.98385	0.1995	19.0	0.02247	1008.0	3557.0	7629.0	9232.0
31	71.17166	0.20504	18.0	0.02179	1039.0	3688.0	7635.0	9226.0
32	71.31381	0.20525	19.0	0.02436	1065.0	3657.0	7615.0	9231.0
33	71.43409	0.21136	19.0	0.02583	1145.0	3657.0	7607.0	9230.0
34	71.47297	0.21097	19.0	0.02581	1144.0	3648.0	7597.0	9232.0
35	71.59574	0.2026	21.0	0.02538	1076.0	3517.0	7569.0	9239.0
36	71.59757	0.14174	27.0	0.01769	600.0	2731.0	7448.0	9263.0
37	71.9048	0.1973	20.0	0.02269	1000.0	3488.0	7614.0	9236.0
38	73.0967	0.16326	24.0	0.01826	757.0	3069.0	7454.0	9248.0
39	73.18824	0.19294	21.0	0.02518	973.0	3459.0	7593.0	9238.0
40	73.33954	0.18893	22.0	0.02217	986.0	3325.0	7515.0	9244.0
41	73.81402	0.16483	24.0	0.01828	776.0	3060.0	7456.0	9249.0
42	73.83524	0.23068	18.0	0.02266	1337.0	3793.0	7500.0	9239.0
43	73.92936	0.18771	22.0	0.02398	950.0	3302.0	7477.0	9238.0
44	74.06774	0.17857	24.0	0.0204	891.0	3234.0	7454.0	9247.0
45	74.10984	0.1756	24.0	0.02056	856.0	3196.0	7342.0	9260.0
46	74.27299	0.22651	18.0	0.02227	1272.0	3780.0	7460.0	9237.0
47	74.5434	0.19064	21.0	0.02292	983.0	3399.0	7549.0	9241.0
48	74.60338	0.19101	21.0	0.02346	968.0	3411.0	7579.0	9231.0
49	74.8586	0.18576	23.0	0.02367	949.0	3281.0	7448.0	9238.0
50	75.26696	0.18119	22.0	0.02033	903.0	3334.0	7446.0	9241.0

line id	extractor	aggregator	distance
1	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean
2	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max
3	pitch_contour_segmentation	octave_abstraction	lcs_circular_max
4	beat_synchronous_chroma_cqt	diff_stats_1	manhattan_distance_oti
5	beat_synchronous_chroma_cqt	diff_stats_1	cosine_distance_oti
6	beat_synchronous_chroma_cqt	statistical_summarization	manhattan_distance_oti
7	beat_synchronous_chroma_cqt	diff_stats_1	euclidean_distance_oti
8	beat_synchronous_chroma_cqt	diff_stats_2	manhattan_distance_oti
9	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_mean
10	beat_synchronous_chroma_stft	diff_stats_1	manhattan_distance_oti
11	beat_synchronous_chroma_cqt	basic_stats_1	manhattan_distance_oti
12	beat_synchronous_chroma_cens	basic_stats_2	manhattan_distance_oti
13	beat_synchronous_chroma_cens	statistical_summarization	manhattan_distance_oti
14	beat_synchronous_chroma_stft	diff_stats_1	euclidean_distance_oti
15	beat_synchronous_chroma_stft	statistical_summarization	cosine_distance_oti
16	chroma_cqt	statistical_summarization	manhattan_distance_oti
17	beat_synchronous_chroma_stft	diff_stats_1	cosine_distance_oti
18	beat_synchronous_chroma_cqt	statistical_summarization	cosine_distance_oti
19	beat_synchronous_chroma_cqt	diff_stats_2	euclidean_distance_oti
20	chroma_cens	statistical_summarization	manhattan_distance_oti
21	beat_synchronous_chroma_stft	statistical_summarization	manhattan_distance_oti
22	beat_synchronous_chroma_cens	basic_stats_2	cosine_distance_oti
23	beat_synchronous_chroma_cens	diff_stats_2	euclidean_distance_oti
24	beat_synchronous_chroma_cens	basic_stats_2	euclidean_distance_oti
25	beat_synchronous_chroma_cens	diff_stats_2	cosine_distance_oti
26	beat_synchronous_chroma_cqt	basic_stats_1	cosine_distance_oti
27	beat_synchronous_chroma_cqt	basic_stats_2	euclidean_distance_oti
28	beat_synchronous_chroma_cqt	diff_stats_2	cosine_distance_oti
29	beat_synchronous_chroma_cens	diff_stats_1	manhattan_distance_oti
30	beat_synchronous_chroma_cqt	basic_stats_2	manhattan_distance_oti
31	beat_synchronous_chroma_cqt	statistical_summarization_2	monte_carlo_distance
32	beat_synchronous_chroma_cqt	basic_stats_1	euclidean_distance_oti
33	beat_synchronous_chroma_cens	diff_stats_1	cosine_distance_oti
34	beat_synchronous_chroma_cens	diff_stats_1	euclidean_distance_oti
35	chroma_cqt	statistical_summarization	cosine_distance_oti
36	beat_synchronous_chroma_stft	diff_stats_2	manhattan_distance_oti
37	beat_synchronous_chroma_cqt	basic_stats_2	cosine_distance_oti
38	beat_synchronous_chroma_stft	basic_stats_1	manhattan_distance_oti
39	chroma_cens	basic_stats_2	manhattan_distance_oti
40	chroma_cqt	diff_stats_1	manhattan_distance_oti
41	beat_synchronous_chroma_stft	basic_stats_1	euclidean_distance_oti
42	beat_synchronous_chroma_cens	vector_quantization	manhattan_distance
43	chroma_cqt	diff_stats_1	cosine_distance_oti
44	chroma_cqt	basic_stats_2	manhattan_distance_oti
45	chroma_stft	statistical_summarization	cosine_distance_oti
46	beat_synchronous_chroma_cqt	vector_quantization	manhattan_distance
47	chroma_cqt	basic_stats_1	manhattan_distance_oti
48	beat_synchronous_chroma_cens	basic_stats_1	manhattan_distance_oti
49	chroma_cqt	basic_stats_1	cosine_distance_oti
50	beat_synchronous_chroma_cqt	diff_stats_1	chebyshev_distance_oti

Appendix C

Cover Song Identification: filtered results per dataset

Covers80

line id	original position	extractor	aggregator	distance				
1	1	chroma_stft	diff_stats_1	cosine_distance_oti				
2	2	chroma_stft	basic_stats_1	cosine_distance_oti				
3	3	beat_synchronous_chroma_cens	basic_stats_2	manhattan_distance_oti				
4	48	chroma_cqt	vector_quantization_default	cosine_distance				
5	69	tonnetz	diff_stats_1	manhattan_distance				
6	125	beat_synchronous_chroma_cens	statistical_summarization_2	monte_carlo_distance				
7	176	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean				
8	202	spectral_contrast	statistical_summarization_2	earth_movers_distance				
9	238	rhythm_histogram	bypass	cosine_distance				
10	312	mfcc	statistical_summarization_2	monte_carlo_distance				
11	320	chroma_stft	gaussian_mixture_model_default	manhattan_distance				
12	387	zero_crossing_rate	basic_stats_1	chebyshev_distance				
13	404	temporal_rhythm_histogram	bypass	cosine_distance				
14	413	pitch_contour_segmentation	markov_chain	circular_manhattan				
15	422	melspectrogram	basic_stats_1	cosine_distance				
16	465	rms	diff_stats_1	cosine_distance				
line id	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
1	41.575	0.19359129898294591	31.0	0.19359129898294591	21.0	46.0	142.0	160.0
2	41.99375	0.19205713147354658	32.0	0.19205713147354658	20.0	44.0	142.0	160.0
3	42.3625	0.2059799332525752	27.5	0.2059799332525752	20.0	56.0	138.0	160.0
4	46.7375	0.2059312990778413	26.5	0.2059312990778413	22.0	51.0	129.0	160.0
5	47.725	0.20149125937259355	34.0	0.20149125937259355	22.0	50.0	136.0	160.0
6	49.675	0.23595776927301804	30.5	0.235957769273018	29.0	48.0	129.0	160.0
7	52.2375	0.17346189194579906	39.0	0.17346189194579903	18.0	46.0	125.0	160.0
8	53.55625	0.06932528652541288	46.5	0.06932528652541288	2.0	25.0	137.0	160.0
9	55.29375	0.16548027920050967	37.0	0.16548027920050964	15.0	44.0	119.0	160.0
10	59.58125	0.0780267105659147	53.5	0.07802671056591469	3.0	23.0	128.0	160.0
11	59.93125	0.0842995286521828	49.5	0.08429952865218279	6.0	24.0	124.0	160.0
12	64.25	0.04185368472571946	58.5	0.04185368472571945	0.0	18.0	121.0	160.0
13	65.40625	0.0812231961881101	56.5	0.0812231961881101	5.0	28.0	111.0	160.0
14	66.425	0.08850042156866501	61.5	0.08850042156866501	7.0	26.0	114.0	160.0
15	66.79375	0.08032600860261674	58.0	0.08032600860261674	3.0	30.0	110.0	160.0
16	69.1	0.051927264847166345	64.5	0.051927264847166345	2.0	20.0	116.0	160.0

YouTubeCovers

line id	original position	extractor	aggregator	distance				
1	1	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean				
2	3	pitch_contour_segmentation	markov_chain	circular_manhattan				
3	4	pitch_contour_segmentation	markov_chain	circular_cosine				
4	5	chroma_stft	statistical_summarization	cosine_distance_oti				
5	8	chroma_stft	diff_stats_1	cosine_distance_oti				
6	53	rhythm_histogram	bypass	cosine_distance				
7	55	temporal_rhythm_histogram	bypass	cosine_distance				
8	119	beat_synchronous_chroma_stft	vector_quantization	cosine_distance				
9	128	chroma_cens	statistical_summarization_2	monte_carlo_distance				
10	160	tonnetz	diff_stats_1	manhattan_distance				
11	272	mfcc	diff_stats_2	manhattan_distance				
12	338	spectral_contrast	vector_quantization	manhattan_distance				
13	362	beat_synchronous_chroma_cqt	gaussian_mixture_model_default	manhattan_distance				
14	376	zero_crossing_rate	vector_quantization	cosine_distance				
15	416	melspectrogram	diff_stats_1	cosine_distance				
16	472	rms	diff_stats_1	manhattan_distance				
line id	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
1	7.9714285714285715	0.694195950993107	1.0	0.3611413162288402	219.0	296.0	345.0	350.0
2	14.1	0.4343951990693004	3.5	0.19221026946238964	110.0	231.0	343.0	350.0
3	14.137142857142857	0.4084621091100449	5.0	0.18049755463666442	103.0	233.0	344.0	350.0
4	14.711428571428572	0.3802132780559847	5.0	0.15415423808967568	85.0	227.0	344.0	350.0
5	16.462857142857143	0.3760507761162201	5.5	0.15219416288390122	86.0	223.0	343.0	350.0
6	21.94	0.4074395921903713	5.0	0.1756347720915198	106.0	230.0	328.0	350.0
7	22.042857142857144	0.3124044938703768	9.0	0.10795068713144258	72.0	177.0	338.0	350.0
8	25.088571428571427	0.3539353998080258	7.0	0.14241939491512148	88.0	197.0	329.0	350.0
9	25.47714285714286	0.42128384147654696	5.0	0.18007922766611834	116.0	210.0	333.0	350.0
10	26.597142857142856	0.4081166554557799	7.0	0.1567165099024276	112.0	197.0	322.0	350.0
11	29.605714285714285	0.20063578123307974	16.5	0.07573634001039234	37.0	136.0	331.0	350.0
12	34.02857142857143	0.13802584574304955	20.0	0.0533298500932552	16.0	113.0	329.0	350.0
13	36.505714285714284	0.1455764224149135	24.0	0.05635003857273054	21.0	108.0	318.0	350.0
14	38.24285714285714	0.129752207125118	22.5	0.04984524115007655	19.0	99.0	324.0	350.0
15	40.30285714285714	0.16630280449839283	26.5	0.05872635321775377	28.0	113.0	313.0	350.0
16	42.22571428571428	0.0967731038801955	30.0	0.043335187664363124	8.0	81.0	319.0	350.0

Covers1000

line id	original position	extractor	aggregator	distance				
1	1	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean				
2	2	beat_synchronous_chroma_stft	diff_stats_1	cosine_distance_oti				
3	3	beat_synchronous_chroma_cqt	diff_stats_1	manhattan_distance_oti				
4	4	rhythm_histogram	bypass	cosine_distance				
5	5	beat_synchronous_chroma_stft	basic_stats_1	cosine_distance_oti				
6	77	beat_synchronous_chroma_stft	vector_quantization	manhattan_distance				
7	79	tonnetz	diff_stats_1	manhattan_distance				
8	120	beat_synchronous_chroma_cens	statistical_summarization_2	monte_carlo_distance				
9	153	pitch_contour_segmentation	markov_chain	circular_manhattan				
10	192	mfcc	diff_stats_2	manhattan_distance				
11	237	temporal_rhythm_histogram	bypass	cosine_distance				
12	300	spectral_contrast	diff_stats_1	manhattan_distance				
13	358	melspectrogram	diff_stats_1	cosine_distance				
14	362	zero_crossing_rate	vector_quantization	manhattan_distance				
15	397	beat_synchronous_chroma_cqt	gaussian_mixture_model_default	manhattan_distance				
16	457	rms	diff_stats_1	cosine_distance				
line id	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
1	144.041	0.25731452650966263	35.0	0.19159219029548544	201.0	366.0	636.0	1000.0
2	175.546	0.09844970693153218	74.5	0.06976594754591697	52.0	188.0	548.0	1000.0
3	180.808	0.13566338863815536	75.0	0.09752269108235948	77.0	249.0	551.0	1000.0
4	181.48	0.15933515394861295	72.0	0.1155220926621667	103.0	261.0	558.0	1000.0
5	183.802	0.08610445614781481	95.0	0.06054288711264856	48.0	155.0	515.0	1000.0
6	207.289	0.1508076412071519	90.5	0.11276374830950303	98.0	254.0	521.0	1000.0
7	208.285	0.13638161157172055	93.0	0.09963829747778567	79.0	243.0	518.0	1000.0
8	220.384	0.1709022228089954	95.0	0.12686316072808287	115.0	274.0	511.0	1000.0
9	226.688	0.09073560197206973	128.5	0.06050511697078355	49.0	168.0	446.0	1000.0
10	232.189	0.04254757122885025	135.5	0.030866077871570693	15.0	78.0	417.0	1000.0
11	242.603	0.09235102738320418	134.0	0.0626979859675943	53.0	162.0	445.0	1000.0
12	263.229	0.04223299953152908	185.5	0.029107544291253885	21.0	72.0	325.0	1000.0
13	284.52	0.03126670487011743	199.5	0.02267257253435587	7.0	72.0	324.0	1000.0
14	285.036	0.028922807159794096	220.5	0.01960640393456891	8.0	58.0	298.0	1000.0
15	296.021	0.03356064205683607	226.5	0.022460320004721118	13.0	64.0	315.0	1000.0
16	314.284	0.020117402933182406	227.0	0.013330911728622089	5.0	24.0	274.0	1000.0

Mazurkas

line id	original position	extractor	aggregator	distance				
1	1	pitch_contour_segmentation	octave_abstraction	levenshtein_circular_max				
2	2	beat_synchronous_chroma_cqt	statistical_summarization	manhattan_distance_oti				
3	6	beat_synchronous_chroma_cens	diff_stats_2	manhattan_distance_oti				
4	8	chroma_stft	statistical_summarization	cosine_distance_oti				
5	38	tonnetz	diff_stats_2	manhattan_distance				
6	75	chroma_cens	gaussian_mixture_model_default	manhattan_distance				
7	140	beat_synchronous_chroma_cqt	vector_quantization	chebyshev_distance				
8	186	pitch_contour_segmentation	markov_chain	circular_manhattan				
9	213	chroma_cens	statistical_summarization_2	monte_carlo_distance				
10	217	melspectrogram	vector_quantization	manhattan_distance				
11	292	spectral_rolloff	vector_quantization	cosine_distance				
12	316	mfcc	statistical_summarization	manhattan_distance				
13	400	zero_crossing_rate	vector_quantization	cosine_distance				
14	402	temporal_rhythm_histogram	bypass	manhattan_distance				
15	464	rms	vector_quantization	manhattan_distance				
16	465	statistical_spectrum_descriptor	bypass	manhattan_distance				
line id	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
1	4.157241882524626	0.9577383028307782	1.0	0.8228559773164656	2561.0	2714.0	2728.0	2739.0
2	4.4647938708500545	0.8734719826453456	1.0	0.3362310327306724	2251.0	2638.0	2722.0	2740.0
3	4.866472090477928	0.8311469882398651	1.0	0.30324688046658543	2067.0	2615.0	2723.0	2739.0
4	4.986501276906239	0.8026359677477967	1.0	0.26729815705459575	1965.0	2593.0	2726.0	2741.0
5	5.791681867931412	0.6857343340317748	1.0	0.18034228169579658	1530.0	2526.0	2719.0	2741.0
6	6.477562933236046	0.5973625789801612	2.0	0.10635890035477422	1241.0	2413.0	2723.0	2741.0
7	7.132068588106531	0.8385448226727465	1.0	0.33731334398935464	2106.0	2604.0	2700.0	2740.0
8	7.771251368113827	0.8426504893474391	1.0	0.41661000115687447	2131.0	2614.0	2710.0	2737.0
9	8.495074790222546	0.9360628322856959	1.0	0.6720956091182665	2474.0	2694.0	2714.0	2734.0
10	8.673112002918643	0.6096829700733601	2.0	0.1548019689852552	1292.0	2390.0	2702.0	2740.0
11	10.503101058008026	0.573401584809108	2.0	0.1334111314624724	1190.0	2314.0	2696.0	2741.0
12	11.142283838015324	0.4944919319993829	3.0	0.12090178522543168	984.0	2161.0	2699.0	2741.0
13	20.43962057643196	0.3767142478440718	5.0	0.07679918614424991	666.0	1832.0	2622.0	2741.0
14	20.968624589565852	0.3679612676368265	6.0	0.06942143636338607	670.0	1716.0	2638.0	2740.0
15	33.84312294782926	0.20316694543216524	14.0	0.03987678159635122	266.0	1176.0	2546.0	2738.0
16	33.91499452754469	0.17980510863409532	16.0	0.03634632496485249	223.0	1092.0	2539.0	2740.0

SHS9K

line id	original position	extractor	aggregator	distance				
1	1	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean				
2	4	beat_synchronous_chroma_cqt	diff_stats_1	manhattan_distance_oti				
3	5	beat_synchronous_chroma_cqt	diff_stats_1	cosine_distance_oti				
4	6	beat_synchronous_chroma_cqt	statistical_summarization	manhattan_distance_oti				
5	31	beat_synchronous_chroma_cqt	statistical_summarization_2	monte_carlo_distance				
6	42	beat_synchronous_chroma_cens	vector_quantization	manhattan_distance				
7	56	tonnetz	vector_quantization	manhattan_distance				
8	128	pitch_contour_segmentation	markov_chain	circular_cosine				
9	229	rhythm_histogram	bypass	cosine_distance				
10	257	mfcc	diff_stats_2	manhattan_distance				
11	272	temporal_rhythm_histogram	bypass	manhattan_distance				
12	309	spectral_contrast	vector_quantization	manhattan_distance				
13	335	melspectrogram	diff_stats_1	manhattan_distance				
14	376	chroma_cqt	gaussian_mixture_model_default	manhattan_distance				
15	409	rms	diff_stats_1	cosine_distance				
16	427	zero_crossing_rate	vector_quantization	manhattan_distance				
line id	MR	MRR	MDR	MAP	Top 1	Top 10	Top 100	Top 1000
1	47.57882834374327	0.40387101631290323	6.0	0.05102021990517946	3008.0	5188.0	8067.0	9265.0
2	62.9398018522507	0.2325521006048516	15.0	0.02777233736708638	1275.0	3990.0	7836.0	9240.0
3	63.73713116519492	0.22735912747253192	16.0	0.028126124449084335	1234.0	3914.0	7809.0	9238.0
4	64.75037691147965	0.22813444987030118	16.0	0.026963736995958533	1265.0	3888.0	7787.0	9237.0
5	71.17165625673056	0.20504453845846535	18.0	0.02178863340674668	1039.0	3688.0	7635.0	9226.0
6	73.83523583889726	0.230680804112545208	18.0	0.022657830647124757	1337.0	3793.0	7500.0	9239.0
7	75.95670902433771	0.24926315829542536	16.0	0.02451538944433362	1465.0	4018.0	7544.0	9222.0
8	85.83469739392635	0.1384805174003356	33.0	0.015509588173725964	626.0	2576.0	6967.0	9248.0
9	98.16121042429464	0.1535710358770886	31.0	0.01805656410673726	760.0	2726.0	6975.0	9202.0
10	101.20019384018953	0.0831217277189994	51.0	0.01172026226874542	293.0	1624.0	6427.0	9265.0
11	103.27019168640965	0.10511802347145303	46.0	0.01206894599791695	430.0	1936.0	6508.0	9240.0
12	110.44841697178548	0.07411622238829096	58.0	0.011169863639562658	246.0	1452.0	6172.0	9253.0
13	115.98847727762222	0.06701057859899788	68.0	0.009699406108035945	233.0	1251.0	5717.0	9270.0
14	120.48212362696532	0.05083783264528273	74.0	0.009386275702521166	138.0	961.0	5571.0	9274.0
15	126.26093043290976	0.055635538594680664	72.0	0.009932140745722282	175.0	993.0	5671.0	9238.0
16	128.12416541029506	0.05927839890991961	71.0	0.010400864265275171	186.0	1101.0	5574.0	9236.0

Appendix D

Cover Song Identification: unique top-50 results

position	MR (median)	MR (median absolute deviation)	extractor	aggregator	distance
1	41.58	36.19	chroma_stft	diff_stats_1	cosine_distance_oti
2	41.99	36.62	chroma_stft	basic_stats_1	cosine_distance_oti
3	42.36	25.68	beat_synchronous_chroma_cens	basic_stats_2	manhattan_distance_oti
4	42.44	27.49	beat_synchronous_chroma_cens	basic_stats_2	euclidean_distance_oti
5	42.46	37.2	chroma_stft	diff_stats_1	manhattan_distance_oti
6	42.68	26.99	beat_synchronous_chroma_cens	basic_stats_2	cosine_distance_oti
7	42.72	33.87	chroma_stft	statistical_summarization	manhattan_distance_oti
8	43.02	37.14	chroma_stft	diff_stats_1	euclidean_distance_oti
9	43.08	31.03	chroma_stft	statistical_summarization	cosine_distance_oti
10	43.36	37.07	chroma_stft	basic_stats_1	chebyshev_distance_oti
11	43.36	37.08	chroma_stft	diff_stats_1	chebyshev_distance_oti
12	43.36	37.09	chroma_stft	basic_stats_2	chebyshev_distance_oti
13	43.45	36.2	chroma_stft	statistical_summarization	chebyshev_distance_oti
14	43.92	38.47	chroma_stft	basic_stats_2	cosine_distance_oti
15	44.5	38.43	chroma_stft	basic_stats_1	euclidean_distance_oti
16	44.53	38.41	chroma_stft	basic_stats_2	euclidean_distance_oti
17	44.78	25.24	beat_synchronous_chroma_cqt	diff_stats_1	cosine_distance_oti
18	44.81	25.59	beat_synchronous_chroma_cqt	basic_stats_1	cosine_distance_oti
19	45.0	26.43	beat_synchronous_chroma_cens	diff_stats_1	cosine_distance_oti
20	45.01	36.2	chroma_stft	statistical_summarization	euclidean_distance_oti
21	45.06	30.92	beat_synchronous_chroma_cens	basic_stats_1	euclidean_distance_oti
22	45.06	31.05	beat_synchronous_chroma_cens	basic_stats_1	cosine_distance_oti
23	45.15	26.32	beat_synchronous_chroma_cens	diff_stats_1	euclidean_distance_oti
24	45.15	37.43	chroma_stft	basic_stats_2	manhattan_distance_oti
25	45.16	37.36	chroma_stft	basic_stats_1	manhattan_distance_oti
26	45.29	38.24	beat_synchronous_chroma_cens	basic_stats_2	manhattan_distance
27	45.37	24.42	beat_synchronous_chroma_cqt	diff_stats_1	manhattan_distance_oti
28	45.38	23.54	beat_synchronous_chroma_cqt	diff_stats_2	manhattan_distance_oti
29	45.46	33.1	chroma_stft	diff_stats_1	manhattan_distance
30	45.62	25.44	beat_synchronous_chroma_cens	diff_stats_2	cosine_distance_oti
31	45.83	25.15	beat_synchronous_chroma_cqt	basic_stats_2	manhattan_distance_oti
32	46.04	39.29	beat_synchronous_chroma_cens	basic_stats_1	cosine_distance
33	46.07	39.33	beat_synchronous_chroma_cens	basic_stats_1	euclidean_distance
34	46.09	37.84	chroma_cqt	diff_stats_1	manhattan_distance
35	46.17	28.43	beat_synchronous_chroma_cens	basic_stats_1	manhattan_distance_oti
36	46.19	39.2	chroma_cens	diff_stats_1	cosine_distance
37	46.2	39.21	chroma_cens	diff_stats_1	euclidean_distance
38	46.22	39.23	chroma_cens	basic_stats_1	cosine_distance
39	46.24	39.24	chroma_cens	basic_stats_1	euclidean_distance
40	46.26	24.61	beat_synchronous_chroma_cens	diff_stats_1	manhattan_distance_oti
41	46.26	38.26	beat_synchronous_chroma_cens	diff_stats_1	cosine_distance
42	46.34	37.97	beat_synchronous_chroma_cens	diff_stats_1	euclidean_distance
43	46.42	39.62	chroma_cens	diff_stats_1	manhattan_distance
44	46.48	25.32	beat_synchronous_chroma_cqt	diff_stats_1	euclidean_distance_oti
45	46.48	38.95	chroma_cqt	diff_stats_1	euclidean_distance
46	46.55	39.74	chroma_cens	basic_stats_1	manhattan_distance
47	46.61	41.75	beat_synchronous_chroma_cens	diff_stats_2	manhattan_distance_oti
48	46.74	37.09	chroma_cqt	vector_quantization_default	cosine_distance
49	46.77	24.02	beat_synchronous_chroma_cqt	basic_stats_2	euclidean_distance_oti
50	46.8	39.94	chroma_cqt	statistical_summarization	euclidean_distance

Appendix E

Cover Song Identification: unique filtered results

original position	MR (median)	MR (median absolute deviation)	extractor	aggregator	distance
1	41.58	36.19	chroma_stft	diff_stats_1	cosine_distance_oti
2	41.99	36.62	chroma_stft	basic_stats_1	cosine_distance_oti
3	42.36	25.68	beat_synchronous_chroma_cens	basic_stats_2	manhattan_distance_oti
48	46.74	37.09	chroma_cqt	vector_quantization_default	cosine_distance
67	47.58	39.61	pitch_contour_segmentation	octave_abstraction	lcs_circular_mean
69	47.72	38.41	tonnetz	diff_stats_1	manhattan_distance
126	49.68	28.96	beat_synchronous_chroma_cens	statistical_summarization_2	monte_carlo_distance
202	53.56	14.32	spectral_contrast	statistical_summarization_2	earth_movers_distance
238	55.29	33.35	rhythm_histogram	bypass	cosine_distance
311	59.58	36.7	mfcc	statistical_summarization_2	monte_carlo_distance
319	59.93	44.35	chroma_stft	gaussian_mixture_model_default	manhattan_distance
386	64.25	22.06	zero_crossing_rate	basic_stats_1	chebyshev_distance
403	65.41	40.87	temporal_rhythm_histogram	bypass	cosine_distance
413	66.42	52.32	pitch_contour_segmentation	markov_chain	circular_manhattan
422	66.79	51.52	melspectrogram	basic_stats_1	cosine_distance
461	69.1	26.23	rms	diff_stats_1	cosine_distance

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