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An approach to the sequential evaluation of emotional behaviors of depressive users on social networks in groups and individually

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Felipe Taliar Giuntini

Uma abordagem para a avaliação sequencial dos comportamentos emocionais de usuários depressivos nas redes sociais em grupo e individualmente

Tese apresentada ao Instituto de Ciências Matemáticas e de Computação – ICMC-USP, como parte dos requisitos para obtenção do título de Doutor em Ciências – Ciências de Computação e Matemática Computacional. *VERSÃO REVISADA*

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Orientadora: Prof. Dr. Jó Ueyama

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To my parents,
to all researchers in Brazil,
to everyone dealing with depression and other mental disorders,
have hope and certainty that better days will come.

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This work is the result of a lot of effort and perseverance spent in recent years. When I wrote these words below, I had a feeling of pride and gratitude to those who contributed throughout the process is inevitable. I want to express my sincere appreciation to:

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"It is no measure of health to be well adjusted
to a profoundly sick society"
(J. Krishnamurti)

RESUMO

GIUNTINI, F. T. **Uma abordagem para a avaliação sequencial dos comportamentos emocionais de usuários depressivos nas redes sociais em grupo e individualmente**. 2021. 169 p. Tese (Doutorado em Ciências – Ciências de Computação e Matemática Computacional) – Instituto de Ciências Matemáticas e de Computação, Universidade de São Paulo, São Carlos – SP, 2021.

O constante crescimento de uso e compartilhamento de dados em redes sociais tem fornecido oportunidades de desenvolvimento de soluções inteligentes para a compreensão de dimensões do comportamento humano online, uma vez que usuários compartilham aspectos sociais, sentimentos e opiniões diariamente. Deste modo, diversos estudos em Computação Afetiva têm sido conduzidos em busca de reconhecer e predizer aspectos emocionais e indicativos de problemas mentais, por meio de mineração de dados complexos, como textos, imagens, vídeos e emoticons, disponibilizados nas postagens de redes sociais. A depressão é um problema comum e crescente de saúde no mundo, sendo considerada a terceira maior causa de incapacidade para o trabalho e a principal causa de emergência nos centros de saúde, caracterizada pela manifestação de um conjunto de sintomas por pelo menos duas semanas. Os sintomas podem ser compostos por profunda tristeza, sentimento de culpa, perda de prazer e características mistas e atípicas, correlacionar à contextos e impactar severamente diversos aspectos sociais. Embora seja necessário a observação de características emocionais ao longo do tempo, pelo que é conhecido na literatura, os estudos tem focado em classificar se uma determinada postagem é depressiva e não têm endereçado o reconhecimento temporal das manifestações de humor, bem como aspectos de personalidade ou contexto. Com isso, esta Tese teve por objetivo responder "como reconhecer padrões temporais de comportamento de usuários depressivos em redes sociais online?" Desta forma, apresenta-se uma abordagem para reconhecimento temporal de padrões de comportamento de usuários depressivos em redes sociais, composta por duas metodologias que permitem (i) a avaliação temporal dos padrões de comportamentos de interações dos usuários em grupo combinando modelagem e métricas de redes complexas e reconhecimento de emoções e sentimentos, e (i) reconhecimento sequencial dos padrões de comportamento dos usuários depressivos individualmente, por meio da minerações de padrões frequentes das características emocionais e de contexto. Em ambas, utilizou-se informações de postagens e comentários, compostos por textos e emoticons presentes na timeline do usuário. A abordagem foi avaliada por meio de métricas de rede complexas e reconhecimento de padrões frequentes, indicando reconhecer fortes padrões de comportamentos interacional, emocional e de contexto online ao longo do tempo, que servem como indicativos para especialistas do comportamento humano e são pautados em evidências na literatura.

Palavras-chave: Computação afetiva, depressão, mineração de padrões sequenciais, redes sociais, análise temporal.

ABSTRACT

GIUNTINI, F. T. **An approach to the sequential evaluation of emotional behaviors of depressive users on social networks in groups and individually**. 2021. 169 p. Tese (Doutorado em Ciências – Ciências de Computação e Matemática Computacional) – Instituto de Ciências Matemáticas e de Computação, Universidade de São Paulo, São Carlos – SP, 2021.

The constant growth in the use and sharing of data on social networks has provided opportunities to develop intelligent solutions for understanding different dimensions of human behavior online since users share social aspects, feelings, and opinions daily. In this way, several studies in Affective Computing have been conducted to recognize and predict emotional and indicative aspects of mental problems through the mining of complex data, such as texts, images, videos, and emoticons, available in social network posts. Depression is a common and growing health problem globally and is considered the third largest cause of incapacity for work, and the leading cause of emergency in health centers is characterized by the manifestation of a set of symptoms for at least two weeks. Symptoms can be compounded by profound sadness, guilt, loss of pleasure and mixed and atypical characteristics, which may be correlated to contexts and severely impact various social aspects. Although it is necessary to observe emotional characteristics over time, as it is known in the literature, studies have focused on classifying whether a given post is depressive and have not addressed the temporal recognition of mood manifestations and aspects of personality context. This Thesis aimed to answer "how to recognize temporal patterns of behavior of depressive users in online social networks?" In this way, an approach for the temporal recognition of behavioral patterns of depressed users on social networks is presented, composed of two methodologies that allow (i) the temporal evaluation of the behavioral patterns of user interactions in groups combining modeling and metrics of complex networks and recognition of emotions and feelings, and (i) sequential recognition of the patterns of behavior of individual depressive users, through the mining of frequent patterns of emotional and contextual characteristics. Information from posts and comments was used in both methodologies, composed of texts and emoticons present in the user's timeline. Through complex network measures and frequent pattern recognition, the approach was evaluated, indicating to recognize strong patterns of interactional, emotional, and contextual behaviors online over time, which serve as indicative for human behavior specialists and are based on evidence in the literature.

Keywords: Affective Computing, Depression, Sequencial Pattern Mining, Social Networks, Temporal analysis.

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LIST OF ABBREVIATIONS AND ACRONYMS

AC	Average Clustering
APA	American Psychiatric Association
API	Application Programming Interface
CCG	Coverage Community Generation
CES-D	Center for Epidemiologic Studies Depression Scale
CGB	Community Growth Behavior
CGP	Community Generation Performance
DM	Diameter
DS	Density
DSM	Diagnostic and Statistical Manual of Mental Disorders
DT	Decision Trees
ECNN	Emotion-Semantic-Enhanced Convolutional Neural Network
EM	Expectation-Maximization
EMUS	Emotional User Score
ESLAM	Smoothed moticon Smoothed Language Model
HSV	Hue, Saturation, and Value
IBL	Instance-Based Learning
ID	user identifier
LIWC	Linguistic Inquiry and Word Count
ME	Maximum Entropy
ML	Machine Learning
MLP	Multilayer Perceptron
MTurk	Amazon's Mechanical Turk
NB	Naive Bayes
NLTK	Natual Language Tookik
PHQ	Patient Health Questionnaire
PrefixSpam	Prefix-projected Sequential pattern mining
PROMIS	Patient-Reported Outcomes Measurement Information System
SMNs	Social Media Networks
SMO	Sequential Minimal Optimization
SMS	Short Message Service

SPL	Average Shortest Path Length
SPSS	Statistical Package for the Social Sciences
SVM	Support Vector Machine
TDC-F	Temporal Dynamic of Communities using F-Score
TSA	Twitter Sentiment Analysis
UBS	Basic Health Units

CONTENTS

CHAPTER 1

INTRODUCTION

Online social networks emerged to facilitate communication and promote the relationship between people and companies. These communication platforms have increasingly gained people and businesses' importance in recent years, significantly impacting user behavior with the emergence of several new features and services. Nowadays, it is possible to notice that online services are intimately present in our day-to-day lives. Users post and share their feelings, opinions, subjects of interest and get informed about the most diverse topics and events, such as news and politics. In most cases, the virtual context merges with the context of authentic (real) human life for modern society.

Several studies have been conducted in order to understand user behaviors and social aspects online, such as how connections and bonds of friendship occur (TODD; BLEVINS; YI, 2020; MANNING, 2020; LEE; BORAH, 2020; STRAUGHAN; BISSELL; GORMAN-MURRAY, 2021), predict elections (Belcastro *et al.*, 2020; CHAUHAN; SHARMA; SIKKA, 2021; SKORIC; LIU; JAIDKA, 2020), make product recommendations (SHEN *et al.*, 2020; TROUDI *et al.*, 2020), among others. In this context, data science approaches have been investigated to extract characteristics, recognize patterns, and make predictions based on the large amount of data produced and shared by users formed by different media, *e.g.* texts, images, audios, emoticons.

Affective Computing is a multidisciplinary area that aims to (i) recognize emotional aspects (Jiang *et al.*, 2017; Kanjo; Kuss; Ang, 2017; Guo *et al.*, 2018; Liu; Jiang, 2019; Zhang, 2020) and (ii) provide intelligent systems that consider emotions in its design process (Zhang *et al.*, 2019; Landowska; Brodny, 2019; Hasan *et al.*, 2020). In the context of social network analysis and affective computing, several computational models have been proposed to classify feelings and emotions and indicate mental disorders, *e.g.* depression, and anxiety. The development of intelligent models can assist specialists in the field, such as analysts and therapists in mental health, to identify indicators early and conduct the necessary intervention.

1.1 Context and Motivation

Mental health, a term used to describe a person's level of cognitive or emotional quality of life, is a concern of Brazil and the world. Mental disorders have been recognized as one of the leading causes of impairment in the physical and cognitive development of quality of life losses due to loss of income due to impact on work activities(World Health Organization, 2020). They affect at least 20% of the world population at some point in life, being the second cause of emergency care. Mood disorders have been listed as one of the main global burdens of disease, affecting more than 264 million people worldwide (World Health Organization, 2020). These disorders have been identified as one of the main causes of absenteeism and presenteeism from work activities, recognized as the third cause of absence from work in Brazil (RAZZOUK, 2016).

Depression has been characterized as a mood disorder in which emotional and motivational conditions would be the most compromised components. In this condition, a relatively persistent feeling of sadness is observed, a decrease in the interest in engaging in activities that would typically be pleasurable, with impairment of routine and daily activities, for at least two weeks. There is also an increase in anxiety, reduced concentration, feelings of guilt, hopelessness and worthlessness, suicidal ideation, among others (KROENKE; SPITZER; WILLIAMS, 2001; American Psychiatric Association and others, 2013; World Health Organization, 2020).

Despite the depression's overwhelming impact on human conditions, its high comorbidity with suicidal ideation and behavior, and its high economic cost, the investment in evaluation and intervention strategies in this condition has been negligible. The study of (CHISHOLM *et al.*, 2016) demonstrated a modeling study about economic return on investment in the treatment of depression, that in countries like Brazil, an investment of 86% or more of current investment would be necessary for the desired archive the goals. Furthermore, it was observed in Brazil, and 35 other countries, that for every dollar invested in expanding the assessment and treatment of this disorder, there would be an economic return of approximately four dollars. However, the network of public services available to care for the condition is still insufficient, *e.g.* in the public health service in São Paulo city, where less than 30% of Basic Health Units (UBS) that offer the primary service in the public network provides the service of psychological/psychiatric care overburdening the public system (SANCHEZ, 2016).

Traditionally, mental health professionals have primarily used clinical examination techniques based on self-reporting of emotional, behavioral, and cognitive dimensions to diagnose and monitor the condition's evolution (e.g., questionnaire, interviews, filling in inventories standardized, among others). However, a new source of self-reported information has been examined to generate subsidies for identifying and tracking the condition: the thousands of data regularly included in social networks. Social networks, such as Facebook and Twitter, have significantly changed how people live. It has become routine to share and record everyday life, whether in public or private social experiences online. The evaluation of information made available in massive data sharing has been an efficient and effective tool in studying different human behavior dimensions, particularly affective dimensions (GREENBLATT; BECERRA; SERAFETINIDES, 1982; KAWACHI; BERKMAN, 2001; HAWN, 2009; MORRIS; TEEVAN; PANOVICH, 2010; GRAJALES *et al.*, 2014; ORGANIZATION *et al.*, 2017; YAZDAVAR *et al.*, 2020).

Accordingly, many mental health professionals and computer scientists have tried to develop techniques and technologies for analyzing information from social networks to investigate the so-called mental phenomena and processes (LUOR *et al.*, 2010; VASHISHT; THAKUR, 2014; GASPAR *et al.*, 2016). Undoubtedly, this interdisciplinary integration has injected new vigor in the field of psychology and computer science.

The use of social networks as another lens in identifying indicators of depressive mood disorders can allow a faster and more accurate diagnosis and follow-up. However, the literary works have focused only on applying algorithms to analyze feelings in posts individually for the best of knowledge. The works do not seek to analyze and interpret the user's previous behavior and do not explain their behavioral patterns on a long-term basis. In contrast, the characterization of depression involves the analysis of persistent symptoms. (World Health Organization and others, 2017; World Health Organization, 2020). Accordingly, this work investigates *"how recognizing temporal patterns of depressive users on social networks?"*.

1.2 Problem Statement

Data science approaches and algorithms have been applied in order to identify feelings and emotions on social networks. In recent years, these algorithms have been explored in the context of recognizing mental health problems, such as depression. Regarding state of the art on recognition of depressive users on social networks, For the best of knowledge the most previous studies focus on the analysis of specific media, *i.e.* text, image, videos, emoticons, or on analysis of log activities and demographic information to classify if a unique post is depressive or not, based on the polarity of sentiment.

However, the computational support suggests is insufficient to analyze depressive mood disorder concerning what is recommended by the World Health Organization (World Health Organization, 2020) and the leading associations in mental health, *e.g.* American and European associations, which establish standards for clinical evaluations in human behavior analysis. It is a consensus among all those mentioned associations that for the evaluation and diagnosis of depressive behavior, it is necessary to observe the manifestation of symptoms and long-term characteristics, mainly observing symptoms persisting for 15 days. This observation usually involves interviews and questionnaires, such as Patient Health Questionnaire (PHQ) (KROENKE; SPITZER; WILLIAMS, 2001; WU *et al.*, 2020) and Patient-Reported Outcomes Measurement Information System (PROMIS) (American Psychiatric Association and others, 2013), for at least 15 consecutive days. Besides, it is suggested to observe aspects of personality and context that can impact feelings (COIFMAN; BONANNO, 2010; SOUTHWARD; CHEAVENS, 2017). In other words, it is suggested that it is not possible to determine based on a single post that the user shows signs of depression since the disease consists of a set of characteristics, requiring the observation of user behavioral patterns over time, observing their timeline and the emotional evolution.

One of the significant challenges in the mining behaviors of social media data users is dealing with complex data, *i.e.* text, emoticons and images, a non-structured database, and the very dynamic environment, *e.g.* users have posting frequencies and characteristics very different individuals and contexts. As a result, black-box approaches and other non-explanatory models can generate a semantic gap and make it challenging to explain behaviors to domain experts. Besides, as the health community suggests, an approach that corresponds to the interest of specialists involves the recognition and extraction of emotional behavior patterns over time so that it is then possible to make a decision and establish the necessary intervention.

To the best of our knowledge, none of the previous works in the literature addresses the longitudinal recognition of behavioral patterns of depressive users on social media considering the analysis of (i) sequential patterns of depressive user-interaction in community with others and (ii) extraction of the sequential pattern of emotional behavior of depressive users' behavior individually.

1.3 Hypothesis and Contributions

In order to fill the research gap mentioned in section 1.2, the following research thesis is defined:

The (i) extraction of emotional characteristics of posts and comments, (ii) mining sequential and individual patterns and (iii) evaluating their interactions modeling by complex networks over time can describe strong behavioral patterns of depressive users on social media.

In order to meet the research hypothesis, this thesis aims to present an approach to the sequential evaluation of emotional behaviors of depressive users on social networks in groups and individually. With this, we highlight the following contributions:

1. A systematic review on recognizing depression in social networks.
2. A fundamental study to recognize emotional expressions in social networks through emoticons and check if there is a correlation between the expression of Ekman's universal emotions (EKMAN, 1993) manifested in the virtual environment with those expressed in the natural environment.
3. A methodology to evaluate the depressive user's interactions over time through complex networks and analyzing feelings.

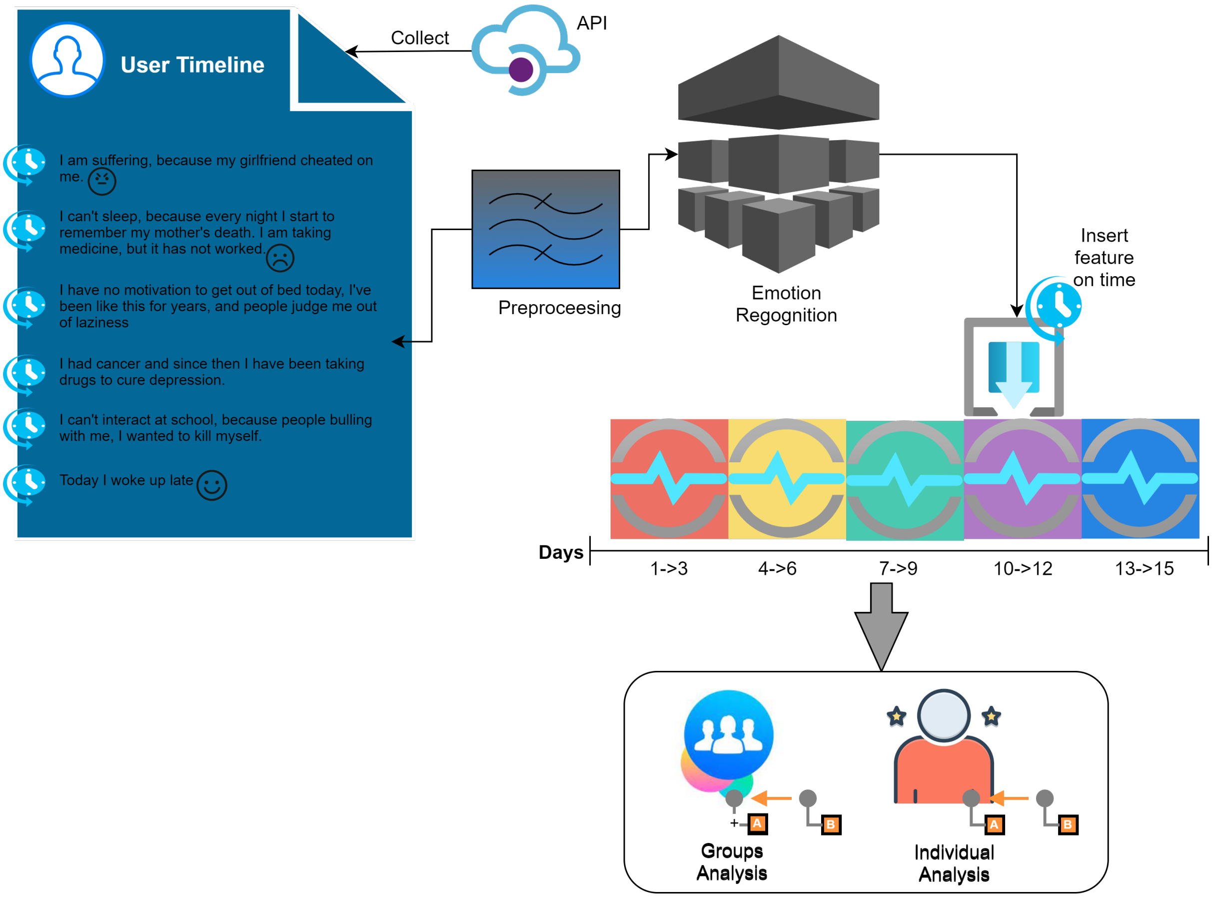

Figure 1 – Overview of the approach to the sequential evaluation of emotional behaviors of depressive users on social networks in groups and individually.

4. The TROAD framework for recognizing the sequential behavioral patterns of depressive users on social networks based on emotional and contextual features presents on user's timeline.

Each contribution above is highlighted in articles form, which makes up each chapter of this thesis. Contribution 1 (described in chapter 3) made it possible to map the state-of-the-art area of computational works that explored depressive aspects in users of social networks. Contribution 2 (described in chapter 4) allowed us to evaluate the potential of using emoticons in analyzing feelings and recognizing emotions, which are used to extract emotions in contributions 3 (described in chapter 5) and 4 (described in chapter 6), which respectively evaluate the behavior of the depressive person in the social network in groups individually. Derived contributions are highlighted in each chapter.

Finally, Figure 1 shows the overview of the approach to the sequential evaluation of emotional behaviors of depressive users on social networks. The pipeline starts with collecting a user timeline that includes the posts and comments formed by texts and emoticons, using an Application Program Interface (API). In sequence, the data are preprocessing using NLP techniques, and we start the emotion recognition of the posts using text and emoticons. The extracted emotional features are inserted in a window of time following the post's moment. Furthermore, we recognize the longitudinal analysis of depressive users (i) in groups using complex network and sentiment analysis metrics and (ii) individually using sequential pattern mining by rules.

It is worth mentioning that this work made a multimode analysis being (i) modeling and recognition of the sequential behavior of interaction of the depressive in groups through complex networks (contribution 3) (ii) extraction of frequent sequential behavior patterns through the extraction of emotional features and context from the user's timeline (contribution 4). In both, texts, emoticons, posts, and comments were used.

1.4 Ethics Committee Approval

This research has the Ethics Committee's approval from the School of Arts, Sciences and Humanities (EACH) of the University of São Paulo, Brazil, under register number 88799118.8.000-0.5390, on the Brazilian Governmental Platform of Health National Council[1].

1.5 Outline:

This Thesis is organized as a collection of articles previously submitted and published in qualified scientific journals following the structure: CChapter 2 discuss the main techniques employed in the methodologies. Chapter 3 shows a systematic review about the previous works on recognition of depression on social networks; Chapter 4 presents a methodology based on clusterization to recognizing the expression of universal and basic emotions using specif emoticons denominated Reactions; Chapter 5 shows and discusses a methodology to recognizing behavioral patterns of depressive users in groups/communities a long term using complex networks and sentiment analysis; Chapter 6 presents a framework to recognizing sequence pattern mining of depressive users on social media considering the emotions and contextual information. Finally, Chapter 5 presents the discussion and conclusions of the work.

[1] <https://plataformabrasil.saude.gov.br/>

CHAPTER

2

FUNDAMENTALS AND METHODS

This chapter discussed the main methods and techniques used in this thesis to clarify details about the approach developed to the sequential evaluation of emotional behaviors of depressive users on social networks in groups and individually.

In summary, the methodology described along with this captures all the posts available on the user's timeline, preprocessing the content to select the texts and emoticons for emotion the following emotion recognition. In the next step, we select and transform our database, transforming the dataset on transaction form, and discretize the time series for better sequential analysis. We employ complex network metrics to analyze the depressive user behavior, and to individual and sequential analysis, we describe sequential patterns in an association rules way.

The discussion is organized following the pipeline provide in Figure 1 that shows following the main steps as preprocessing 2.1, emotion recognition 2.2, and the sequential pattern mining of depression in groups and individually 2.4.

2.1 Text Preprocessing

Before we conduct emotional recognition, we need to discretize the postings to optimize the emotional feature extraction process. For this the we employ Natual Language Tookik (NLTK) (LOPER; BIRD, 2002; BIRD, 2006) in preprocessing methods discussed in Chapters 5, and 6. NLTK is a toolkit available on <nltk.org>, that provides an interface to more than fifty lexical and corpus and text libraries to prepare the texts for some classification, e.g., stemming, tokenization, among others.

We use NTLTK (LOPER; BIRD, 2002) for data cleaning and transformation. We explore in mentioned preprocessing methods: the removal of HTML formatting tags from the texts, for example, "<i> I'm boring</I>" to "I'm boring"; the removal of special characters, i.e., `#@*?()`; the transforming all data in lowercase, and removal of terms that are not meaningful or the

Figure 2 – Empath development (Fast, Chen and Bernstein (2016), p.2)

emotional analysis (e.g., is, or, a,), stemming and lemmatization textual information. This data cleaning process is widely known in the literature as a critical step to optimizing the results of classification problems in text-mining (SARAVANAN; RAJ; RAMAN, 2003; XIE *et al.*, 2020; JAIN *et al.*, 2020; FONSECA *et al.*, 2021).

Although we opted to maintain the emojis e emoticons in our dataset, they contributed to sentiment analysis and emotion recognition. The contributions of emoticons are discussed in Chapter 4.

2.2 Sentiment Analysis and Emotion Recognition text-mining approaches

The methods described in 5.2 6.3 employ two mainly techniques for emotional feature extraction. The technique Vader (HUTTO; GILBERT, 2014a) estimates the polarity of the sentiment, and Empath (FAST; CHEN; BERNSTEIN, 2016) for emotional feature extraction. The details about the techniques are discussed below:

- **VADER** is a sentiment analysis base-rule algorithm [1] implemented in Python that estimates the polarity of the text between -1(more negative) and +1 (more positive). The method is based on counting emotional key-terms in expression and comparing if these terms in a dictionary provide punctuation, which informs how much a text falls into fours categories: positive, neutral, negative. Additionally, VADER informs the compound score, that is, the sum f the lexicon ratings (HUTTO; GILBERT, 2014a; ELBAGIR; YANG, 2019).

- **Empath** is a neural network-based lexicon. He was trained with over 600,000 fiction stories, which formed over 1.8 billion word embeddings. Empath starts creating a vector space from these embeddings that measure the similarity between the words, uses seed terms to define and discover new words for each of its categories. Finally, the authors filtered the categories using crowd-sourcing (FAST; CHEN; BERNSTEIN, 2016). Figure 2 presents the process of development of Empath.

[1] VADER is available at: https://github.com/cjhutto/vaderSentiment

Empath provides 200 categories pre-validate for humans. These categories are about different topics (e.g., politics, college, banking, money, violence, white-collar job), sentiments, and emotions (e.g., sadness, depression, shame, joy). Empath provides us a ranked list of categories with several expressions or terms that assign the respective classification based on an English text. In addition, the developer may generate new specifics categories based on the number of terms following their interest.

We select just the five most ranked categories in our experiments. The authors provided an Application Program Interface (API)[2] implemented in Python. In addition an interactive demo application[3] is provide online.

2.3 Complex Networks for group analysis and user interaction behavior

The Virtual Social Network is understood as a set of actors (nodes) and a set of relationships connecting these actors, that is, edges (TINDALL; WELLMAN, 2001). A node can be understood as different components of a network, such as users and posts. Meanwhile, there are examples of edges, friendships, *likes*, shares, among others. As in real life, this is how communities are built on social networks through relationships.

Several approaches from different areas of knowledge have been developed to understand better the behavior patterns and structures present in virtual social networks. It is far known that depression can be related, started, or promoted in determined contexts, as colleges, works, among others. With this, interpret these contexts and situations is essential for the early identification of symptoms and understating the different aspects of manifestation of depression and how the behavior of interaction of users depressives on social media. In Chapter 5 we model and evaluate the interaction bahevior of depressed users in social networks combining the metrics of complex networks and sentiment analysis in our method.

We model the connections based on interactions of the users, and employ the Crauset-NewmanMoore modularity Maximization method (CLAUSET; NEWMAN; MOORE, 2004; NEWMAN, 2010; NEWMAN, 2012). In sequence, we apply the follow network graph metrics: Assortativity Degree (NEWMAN, 2002; NEWMAN, 2003), Density (NEWMAN, 2012), Average Clustering (SARAMÄKI *et al.*, 2007), Diameter (BARABÁSI; ALBERT; JEONG, 2000), Average Shortest Path Length (BARABÁSI; ALBERT; JEONG, 2000), Community Generation Performance (FORTUNATO, 2010), Community Growth Behavior(SALVE; GUIDI; MICHIENZI, 2018; GUIDI; MICHIENZI; SALVE, 2020), and F-Score. The values of the metrics are compared with emotions manifested in the same period to recognized correlation

2 Empath API available at <https://github.com/Ejhfast/empath-client>
3 Empath Demo application available at <http://empath.stanford.edu/>.

patterns between sentiments and interactive forms for depressed users. The methods and metrics are detailed discussed in section 5.2.

2.4 Sequence Pattern Mining

Sequence pattern mining recognizes sub-sequences of patterns on a sequential database. The most popular methodologies are based on association rules, and their implementations follow the strategies of the Apriori algorithm, which optimized the combinations required for analysis. These methods discover patterns in different applications, like politics, purchase behavior, access patterns, medical treatments.

To evaluate the main symptoms and diagnosis the depression, as discussed in section 1.2 it is crucial the longitudinal and sequential observation of sentiments and emotions demonstrated by a patient or a user in social network (World Health Organization, 2020).

To recognize the sequential patterns of depressed users on social networks, considering the temporal order between patterns in form $A \rightarrow B \rightarrow C$, that each variable is a context or emotion demonstrate by a user, the method described in section 6.3 implements the Prefix-projected Sequential pattern mining (PrefixSpam) (HAN *et al.*, 2001). PrefixSpam fit this gap because can mine the sequences with good performance compared with other based association rule and Apriori solution. We mining the timeline of a user for 15 days, as recommended by WHO, and main statistical questionnaires use to support the diagnosis of mental health (American Psychiatric Association and others, 2013; KROENKE; SPITZER; WILLIAMS, 2001).

For the same sequence database, as showned by Han *et al.* (2001), PrefixSpam follows the main steps:

- **Finding length-1 sequential patterns:** Scan the database with the objective to find all frequent items in sequences counting the support associate.
- **Divide search space:** divide all sequential patterns considering the number of prefixes.
- **Find subsets of sequential patterns:** mining the the subsets of sequential patterns recursively.

The measures of interest to evaluate the sequences and select strong patterns are support, confidence, and sequence confidence. These metrics are discussed in Chapter 5.2.

2.5 Conclusions

This Chapter presented the main techniques and approaches employed in the research methodology to provide a background and support the understanding of the specific chapters.

In summary, the methods for text preprocessing (2.1), and emotion recognition and sentiment analysis (2.2) are employed in methodologies of Chapters 2.3 and 6. The complex networks methods are employed in 5 and the sequence pattern methods are used in 6. Other details are mentioned in appropriate Chapters.

CHAPTER

3

A REVIEW ON RECOGNIZING DEPRESSION IN SOCIAL NETWORKS: CHALLENGES AND OPPORTUNITIES

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- **Abstract:** Social networks have become another resource for supporting mental health specialists in making inferences and finding indications of mental disorders, such as depression. This paper addresses the state-of-the-art regarding studies on recognition of depressive mood disorders in social networks through approaches and techniques of sentiment and emotion analysis. The systematic research conducted focused on social networks, social media, and the most employed techniques, feelings, and emotions were analyzed to find predecessors of a depressive disorder. Discussions on the research gaps identified aimed at improving the effectiveness of the analysis process, bringing the analysis close to the user's reality. Twitter, Facebook, Blogs and Forums, Reddit, Live Journal, and Instagram are the most employed social networks regarding the identification of depressive mood disorders, and the most used information was text, followed by emoticons, user log information, and images. The selected studies usually employ classic off-the-shelf classifiers for the analysis of the available information, combined with lexicons such as NRC Word-Emoticon Association Lexicon, WordNet-Affect, Anew, and LIWC tool. The challenges include the analysis of temporal information and a combination of different types of information.

- **keywords:** depressive disorders, affective computing, mental health, sentiment analysis, emotion recognition, social media, social networks, user behavior.

3.1 Introduction

The area of data science has emerged and expanded towards meeting the growing volume of data and their required computational analysis capability. Approaches and algorithms of machine learning and data mining enable the extraction of information from large complex data sets. Such approaches have been reoriented to this new environment and used for both data interpretation and creation of predictive models in financial (Idrees; Alam; Agarwal, 2019), political (JUNGHERR, 2016), medical (CAZZOLATO *et al.*, 2019b), and criminal (HUANG *et al.*, 2018) domains. Regarding their use in the areas of physical and mental health, data science methodologies have also enabled the extraction of large sets of data for identification of patterns and accumulation of significant knowledge (CORTéS *et al.*, 2015; GIUNTINI *et al.*, 2019; HERLAND; KHOSHGOFTAAR; WALD, 2014).

Although widely discussed, depression is popularly known as the disease of the century, as it has already been a concern pointed out by researchers. For instance, (CDC, 2001) and (LUOMA; MARTIN; PEARSON, 2002) highlighted depression affected approximately 27 million Americans and could be related with over 30,000 suicides each year. In a projection for the next 20 years (MATHERS; LONCAR, 2006), depression would be the leading cause of disability in high-income countries, as the United States, and in 2014 it is one of the most costly worldwide diseases (Centers for Disease Control and Prevention and others, 2014). Despite its overwhelming impact on human conditions, its high co-morbidity with suicidal ideation and behavior, and its high financial cost, the investment in evaluation and intervention strategies have been too little. In a study about the economic return of investment in the treatment of depression, (CHISHOLM *et al.*, 2016) have shown that in countries such as Brazil, it would be necessary a contribution of 86% or more of the current investment to deal with this issue.

According to (RC *et al.*, 2003) and (GONZÁLEZ *et al.*, 2010), although several primary care programs have been designed for detection and treatment, the majority of Americans with symptoms of depression did not receive treatment or the treatment was insufficient. Additionally, minority ethnic groups, such as Mexican Americans and African Americans, are significantly less likely to receive anti-depression therapies than other ethnic groups. In 2017, the World Health Organization (WHO) reported the total number of people living with depression worldwide was 322 million, and the estimated total number of people living with depression increased 18.4% between 2005 and 2015 (World Health Organization and others, 2017).

Data analysis techniques can automatically identify disturbances, based on indicators and symptoms of depressive disorders (American Psychiatric Association and others, 2013). Abnormal patterns in behavior can be recognized in online social networks through data mining techniques, sentiment analysis, and recognition of emotions (MORENO *et al.*, 2011). Although the current performance of predictive models is considered suboptimal, reliable models eventually could detect depressive mood disorders early, thus, paving the way for fast interventions and promotion of relevant public health solutions.

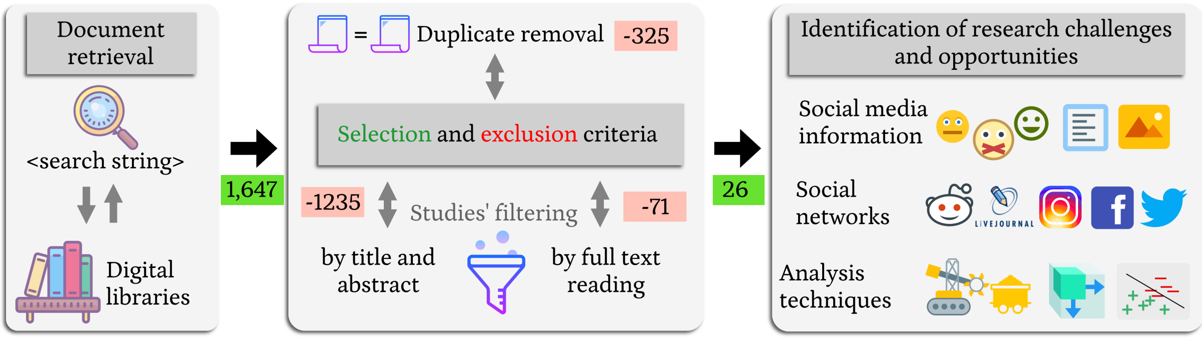

Figure 3 – Summary of the current study. The green boxes show the number of studies moving from one step to the next. Red boxes inform the number of excluded studies by each criterion.

The work in (GUNTUKU *et al.*, 2017) presents a previous review of the use of social media for the detection of depression and mental illness. The authors focused on the Facebook and Twitter social medias. Although their findings are promising, they only considered the analysis of depression and did not discuss the sentiments, emotions, and other disorders that usually come along, as discussed in this paper.

The current paper investigates the state-of-the-art of how sentiment and emotion analysis approaches can identify depressive disorders in social networks. Figure 3 summarizes the steps and goals of our literature review process. Subsequent to retrieving the studies from the leading digital libraries, we employed selection and exclusion criteria and obtained the studies which were further analyzed. We aim to answer the three following questions:

1. Which types of *social media* information were adopted for the identification of depressive mood disorders?

2. Which *social networks* were explored in the identification of depressive mood disorders?

3. What *state-of-the-art techniques* have been employed for the identification and classification of depression for each *social media*?

Paper outline. The remaining parts of the paper are organized as follows: Section 3.2 describes the relevant background on depressive disorders. Section 3.3 presents the method applied in the systematic review that includes search strategy, selection criteria, and data extraction. Section 3.4 provides the systematic review results and an overview of studies conducted, the social media and social networks employed, and the sentiments and emotions analyzed. Section 3.5 discusses research questions and opportunities in the area of recognition of depressive mood disorders from a computational and psychological point of view. Finally, Section 3.6 gives the conclusions.

3.2 Background - Depressive Disorders

The (World Health Organization and others, 2017) characterize depressive disorders as follows: composed of sadness, loss of interest or pleasure, feelings of guilt or low self-esteem, sleep or disturbed appetite, feeling tired, and lack of concentration. Besides, depression can be long-lasting or recurrent, substantially impairing an individual's ability to function at work or school or deal with daily life. In its most severe form, depression can lead to suicide.

The American Psychiatric Association recommends the use of the most recent edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM) (American Psychiatric Association and others, 2013), for the evaluation and diagnosis of the depressive status by mental health professionals. (DUAILIBI; SILVA, 2014) argue that major depressive disorder is composed of at least five of the following symptoms, present for at least two weeks, and which represent changes in the prior functioning of the individual. Since at least one of the symptoms are i) depressed mood or ii) loss of interest or pleasure.

- Depressed mood in most days, almost every day (e.g., feeling sad, empty or hopeless) by subjective observation or by third parties;
- Accentuated decrease in pleasure or interest in all or almost all activities most of the day, almost every day;
- Significant loss or gain in weight without being on a diet (e.g., change in more than 5% of body weight in a month), or increased or decreased appetite almost every day. In children, consider the inability to present the expected weight gains;
- Insomnia or hypersomnia almost every day;
- Psychomotor restlessness or retardation almost every day;
- Fatigue and loss of energy almost every day;
- Feeling of worthlessness or excessive or inadequate guilt, almost every day;
- Reduced ability to think or lack of concentration or indecision, almost every day;
- Recurrent thoughts of death, recurrent suicidal ideation without a specific plan, or attempted suicide or specific plan to commit suicide.

Additionally, the authors emphasize that it is possible to add information in the diagnostic process, called specifiers. These specifiers allow a better characterization and prognosis of each case:

- **Anxiety characteristics:** Demands the presence of at least two of the following symptoms on most days: feeling tense; restless; difficulty concentrating due to concerns; fear that something terrible will happen; control loss feelings. In cases where two symptoms are present, it is considered mild; three is moderate; four or five is moderate to severe; and with motor agitation is severe.

- **Mixed characteristics:** At least three of the following symptoms of mania and hypomania should be present almost every day during an episode of major depressive disorder: elevated mood, high self-esteem; more speech than usual or greater speech pressure; escape from ideas or subjective experience that thoughts are accelerated; increased energy for a specific activity (social, work, school or sexual); excessive involvement in activities of high potential for harmful consequences, such as excessive purchases, sexual indiscretion, unplanned investment; sleeplessness.

- **Melancholic characteristics:** At least one of the following symptoms: loss of pleasure in most activities; and lack of reaction to usually enjoyable activities. Also, three (or more) of the following symptoms: depressed mood characterized by profound dejection; worsens symptoms in the morning; terminal insomnia; restlessness or psycho-motor retardation; significant loss of appetite or anorexia; excessive or inappropriate guilt.

- **Atypical characteristics:** Mood reactivity (improvement with stimuli) or two (or more) of the following symptoms: increased appetite or weight gain; hypersomnia; feeling of weight in the legs or the arms, besides lack of energy; a lasting pattern of sensitivity to social rejection, resulting in significant social prejudice.

- **With psychotic delusions or seasonal patterns:** delusions related to depression or depressive disorder only in specific periods of the year.

This complex set of symptoms has been associated with a substantial loss in quality of life indicators. We usually observe a cause of significant distress or impairment in social, occupational, or even other essential areas of the individual's life (DUAILIBI; SILVA, 2014). Moreover, studies examining the relationship between depression and poverty conditions have indicated that the prevalence of depression may represent economic impacts similar to natural disasters, civil conflicts, or abrupt changes in society. The study seems to indicate that the higher the scores obtained in the depression's indicator were related to a less amount of time devoted to work, lower total expenditure, and reduced investment in education. However, tobacco consumption was higher in this population (BARRETT *et al.*, 2019).

The (American Psychiatric Association and others, 2013) is offering several "emerging measures" for future research in clinical evaluations for a standardized and accurate diagnosis. These measures were developed to be administered at the initial interview with the patient and monitor the progress of the treatment. They should also be used in research and evaluation for potentially improving clinical decision-making, and not as the sole basis for a clinical diagnosis.

The PROMIS Emotional Distress-Depression form[1], for example, is a useful tool for the mental health professional to confirm the presence or absence of depressive disorder, as well as its level. The patient answers a set of eight questions on the frequency he/she has been bothered by a list of "negative feelings" during the last week. The choices of answers range among never, rarely, sometimes, often and always.

3.3 Method applied in present study

This section presents the method employed for the development of a systematic review on the identification of depressive mood disorders in online social networks. The procedure supported by Parsifal tool[2], which follows the guidelines reported in (BARBARA; CHARTERS, 2007), and a protocol was defined for the development of this review.

3.3.1 Search Strategy

The following search string answered the three research questions reported in Section 3.1:

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((sentiment* OR emotion*)
AND (depression OR dejection OR valley OR doldrums OR
prostration OR megrim OR low-spiritedness)
AND ("social network" OR "online community*" OR "social media"))
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The primary studies that identified depression in online social networks were retrieved, and the feelings and emotions recognized in the process, along with the techniques employed, were then obtained. The search was conducted in November 2018. The studies were collected in the following digital databases and with no restriction of publication period: ACM Digital Library, Compendex, IEEE Digital Library, ISI Web of Science, Science Direct, Scopus, Springer Link, and Taylor, and Francis Online. Specifically, at the Springer database, we chose to filter studies from the area of computer science only, due to the high number of studies returned without this filter, which was more than 10 thousand ones.

3.3.2 Selection Criteria

After a systematic reading of the titles and abstracts of the studies, the inclusion criterion adopted was the selection of *only primary studies that infer depression in social networks through the analysis of feelings and recognition of emotions*. This only criterion guided the identification of studies that could provide direct evidence on the research questions. Studies that (i) do not deal with computational aspects, (ii) do not characterize a primary study, (iii) do not propose a

[1] Available online in <http://www.dsm5.org/Pages/Feedback-Form.aspx>
[2] Available at parsif.al

computational approach or method that infers depressive disorders in online social networks, (iv) are duplicate, that is, they have already been evaluated, were excluded.

3.3.3 Data Extraction

After selecting the studies and obtaining the set of studies that had met the inclusion criteria, data were extracted through a complete reading of the selected studies. An extraction form with the following questions was defined: (i) To which social network was the study applied? (ii) What social media were considered in the study? (iii) Does the study identify emotions or feelings? If so, which ones? (iv) Apart from depressive aspects, what other disorders are inferred by the study? (v) What is the main methodology employed?

3.4 Results

This section addresses the literature review conducted. First, we give an overview of the way the studies were obtained. We also present the exclusion criteria considered in this work. Each selected study is then presented, along with a brief description of its main objective. Since we are interested in studies regarding the recognition of depression in social networks, we introduce the social network and the information type used by the selected studies. Finally, we address the considered sentiments, emotions, and other disorders.

3.4.1 Overview of the Studies

Figure 5 depicts the proportion of studies returned per digital database, according to the search string. A total of 1,647 studies were obtained, most of which from Springer Link (36.1%), Scopus (24.1%) and ISI Web of Science (16.3%), followed by Taylor Francis Online (3.7%), El Compendex (3.5%), IEEE Digital Library (1.5%) and ACM Digital Library (0.7%).

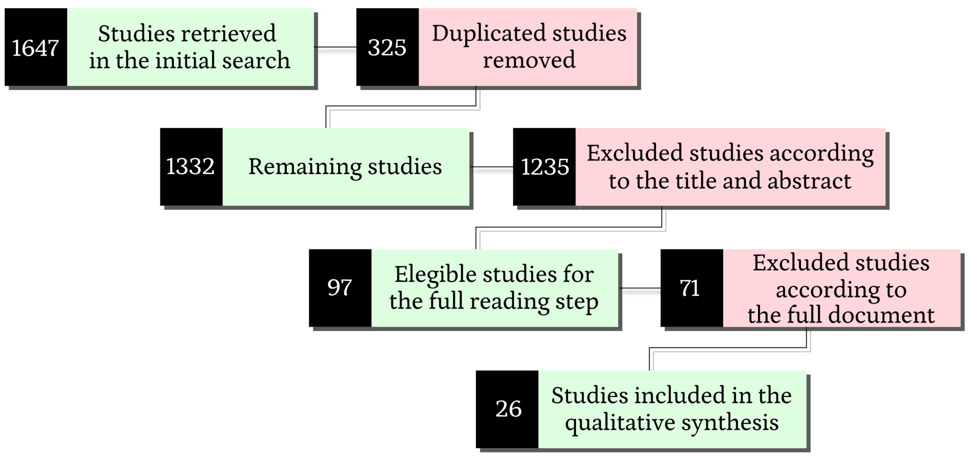

Figure 4 – PRISMA Flow of the literature review.

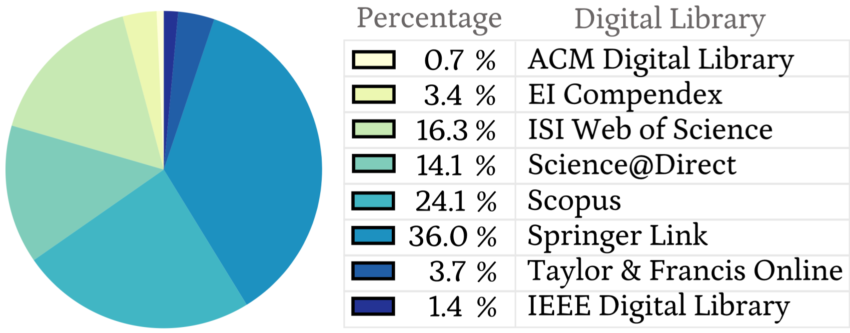

Figure 5 – Portion of studies retrieved from each digital library considered in our work.

Figure 4 shows the PRISMA diagram (LIBERATI *et al.*, 2009), which covers all stages of the selection process, following the methodology presented in Section 3.3. On the left side (green boxes) is the number of selected studies, and on the right side (red boxes), we show the studies removed in each step. Initially, 325 duplicate studies were removed. Duplication occurs because the study can be indexed in more than one digital base concomitantly. A total of 1,235 studies were excluded from the 1,332 selected ones, considering the title and abstract reading step, which resulted in only 97 studies eligible for a full reading. Other 71 studies that did not meet the inclusion criteria during the full reading phase were excluded from the 97 initially eligible ones, and only 26 primary studies were included in the qualitative synthesis.

We examined the studies towards answering the inclusion and exclusion criteria (described in Section 3.3.2). They were annually distributed as follows: 5 in 2013, 1 in 2014, 2 in 2015, 1 in 2016, 15 in 2017, and 2 in 2018. Table 1 shows the authors and the objective of each study. Table 2 summarizes the social networks, the type of media explored, the methods employed, the sentiments, emotions, and other disorders approached in each study considered in the review. We discuss each of these aspects in the next subsections.

3.4.2 Social networks Used in the Studies

Figure 6 shows the most used social networks detected in the studies considered in our review. Twitter is the most explored social network. Studies that rely only on Twitter as a data source are (CHOUDHURY; COUNTS; HORVITZ, 2013; WANG *et al.*, 2013; CHOUDHURY *et al.*, 2013a; BIRJALI; BENI-HSSANE; ERRITALI, 2017; SHEN *et al.*, 2017; VEDULA; PARTHASARATHY, 2017a; LACHMAR *et al.*, 2017). In their work, (HASSAN *et al.*, 2017) combined Twitter with another local social network, and (JUNG; PARK; SONG, 2017) built their dataset combining data from Twitter, Blogs and Forum, and another local social network.

(SEABROOK *et al.*, 2018) explore data from Twitter and Facebook, and the studies (PARK *et al.*, 2013; WEE *et al.*, 2017a; POLIGNANO *et al.*, 2017a; OPHIR; ASTERHAN; SCHWARZ, 2017) use only Facebook, which is the second most adopted social network. Facebook has a large number of features available, and it also allows the analyst to verify user behavior by verifying users' timeline information. Particularly for the behavior analysis area in the Psychology field, the provided information by Facebook allows a better understanding of depressive behavior, since it is possible to combine and merge different types of complex data. On the other hand, the experience of relying on Facebook can be challenging given that the corporation is continuously changing its privacy policies, which often requires periodic changes in the applications, making it harder to maintain an online solution for a long time without proper updates.

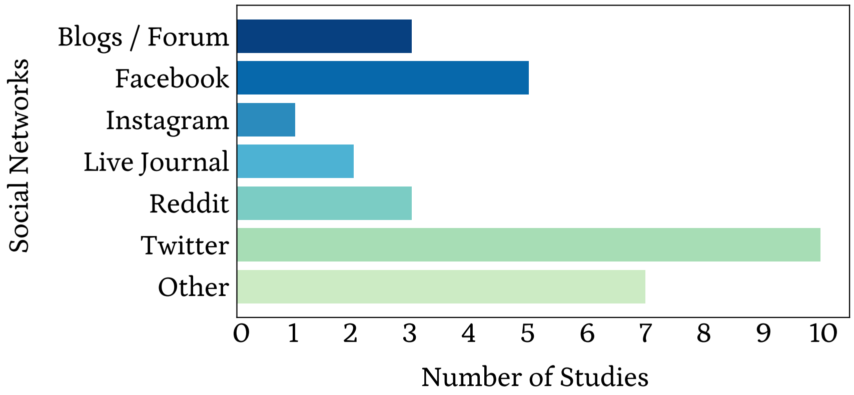

Figure 6 – Social networks approached in the studies.

The works (PARK *et al.*, 2013; LEIVA; FREIRE, 2017; PARK; CONWAY, 2018) considered Reddit, which is a worldwide social network with communities of depression, anxiety, stress, and happiness. It enables studies focused on communities with specific themes, and its great advantage is that communities (called *subreddits*) use slightly more formal and structured English sentences as a way of communication. Such sentences ensures the development of scientific studies in the area of text analysis and natural language processing, since the pre-processing of the content becomes less tedious. Furthermore, the official Reddit API data collection is made easier compared to other social networks.

In (REECE; DANFORTH, 2017) the authors conducted a study with the photo-sharing social networking Instagram, which poses some bureaucracies for the access to users' content. According to (STATISTA, 2018), Instagram gains approximately 1 billion active users worldwide every month. The work conducted by (REECE; DANFORTH, 2017) needed the help of volunteers to answer a survey and share their data using Amazon's Mechanical Turk (MTurk), word cloud platform, to overcome the limitations of access. At MTurk, registered users get paid to answer surveys of their interest.

ID	Authors	Objective
1	(CHOUDHURY; COUNTS; HORVITZ, 2013)	Use of SVM classifier for checking Twitter posts that indicate depression and proposal a of metrics that measures the index of depression.
2	(XU; PHAN; TAN, 2013)	Proposal and evaluation of a new theory on the contagion of depression in social networks.
3	(WANG *et al.*, 2013)	Application of data mining methods for the detection of depressed users in social networking services.
4	(CHOUDHURY *et al.*, 2013a)	Exploration of the potential use of social media for the detection and diagnosis of depressive disorders.
5	(PARK *et al.*, 2013)	Development of a Web application that identifies features related to depressive symptoms on Facebook.
6	(CHOMUTARE, 2014)	Evaluation of text classification methods to identify patients with risk of depression.
7	(SEMENOV *et al.*, 2015)	Investigation of methods and metrics published regarding the analysis of a community of depression in Russian social network VKontakte.
8	(KARMEN; HSIUNG; WETTER, 2015)	Development of a method that detects symptoms of depression in free text.
9	(TUNG; LU, 2016)	Investigation of text mining methods that analyze and predict depression trends in web postings.
10	(PARK; CONWAY, 2017)	Investigation of longitudinal changes in psychological states, which manifest themselves through linguistic changes in members of a community of depression.
11	(BIRJALI; BENIHSSANE; ERRITALI, 2017)	Search for feelings of depression in Twitter users' activities for the estimation of their depressive tendencies.
12	(WEE *et al.*, 2017a)	Demonstration of the interaction between depression and personality based on behavioral data from Facebook users.
13	(NGUYEN *et al.*, 2017)	Exploration of the textual evidence of online communities interested in depression.
14	(REECE; DANFORTH, 2017)	Application of machine learning tools for a successfully identification of markers of depression in Instagram photos.

Table 1 continued from previous page

ID	Authors	Objective
15	(VEDULA; PARTHASARATHY, 2017a)	Observational study for the understanding of interactions between clinically depressed users and their ego-network, in contrast to a differential control group of normal users and their ego-network.
16	(SHEN *et al.*, 2017)	Timely depression detection via harvesting of social media data.
17	(LEIVA; FREIRE, 2017)	Analyses of messages that a user posts online during a time period and detect the risk of depression.
18	(HASSAN *et al.*, 2017)	Detection of a person's level through the extraction of emotions from the text.
19	(FATIMA *et al.*, 2017)	Use of user-generated content for the identification of depression and further characterization of its degree of severity.
20	(POLIGNANO *et al.*, 2017a)	Description of an architecture model that identifies some warning scenarios of blue feelings in Facebook posts.
21	(OPHIR; ASTERHAN; SCHWARZ, 2017)	Comparison of the traditional offline clinical picture of depression with its online manifestations, and exploration of unique features of online depression that are less dominant offline.
22	(LACHMAR *et al.*, 2017)	Examination of the public discourse of the trending hashtag #MyDepressionLooksLike towards a closely at how users talk about their depressive symptoms on Twitter.
23	(CHENG *et al.*, 2017)	Exploration computerized language analysis methods can assess one's suicide risk and emotional distress in the Chinese social media.
24	(JUNG; PARK; SONG, 2017)	Refining of an adolescent depression ontology and terminology as framework for analyses of social media data and evaluation of description logic between classes and the applicability of this ontology to sentiment analysis.
25	(SEABROOK *et al.*, 2018)	Report of associations between depression severity and variability and instability in emotion word expression on Facebook and Twitter across status updates.
26	(PARK; CONWAY, 2018)	Investigation written communication challenges manifest in online mental health communities focusing on depression, bipolar disorder, and schizophrenia.

Table 1 – Overview of the selected studies.

The remaining studies were limited to the use online virtual communities little-known worldwide, or of a more public restricted social network, such as the Live Journal Platform[3], which was used in (NGUYEN *et al.*, 2017; FATIMA *et al.*, 2017); the Psycho-Babble Grief[4], used in (KARMEN; HSIUNG; WETTER, 2015); and VKontakte.We[5], a Russian network used in (SEMENOV *et al.*, 2015). Live Journal Platform is similar to Reddit, since it has non-specific content. Psycho-Bable is focused on the discussion of psychological problems, providing mutual support, and VKontakte.We is similar to Facebook regarding its supported resources and layout structure.

More generally, (TUNG; LU, 2016) explored web postings as a whole, such as blogs and sites, and (CHOMUTARE, 2014) compared postings from a local specific diabetes community. (XU; PHAN; TAN, 2013; CHENG *et al.*, 2017) did not specify the social network used in their study.

3.4.3 Social Media and Techniques Employed in the Studies

The recognition of mood depressive disorders taking advantage of the analysis of social media content has grown in recent years. Figure 7 shows a summary of the use of social media in the selected primary studies. "Study ID" (represented by the horizontal axis) refers to the number of each study, which corresponds to the ones reported in Table 1. The information types used in the studies and extracted from social media are represented by different symbols, which denote text, log files, images, and emoticons in the analysis.

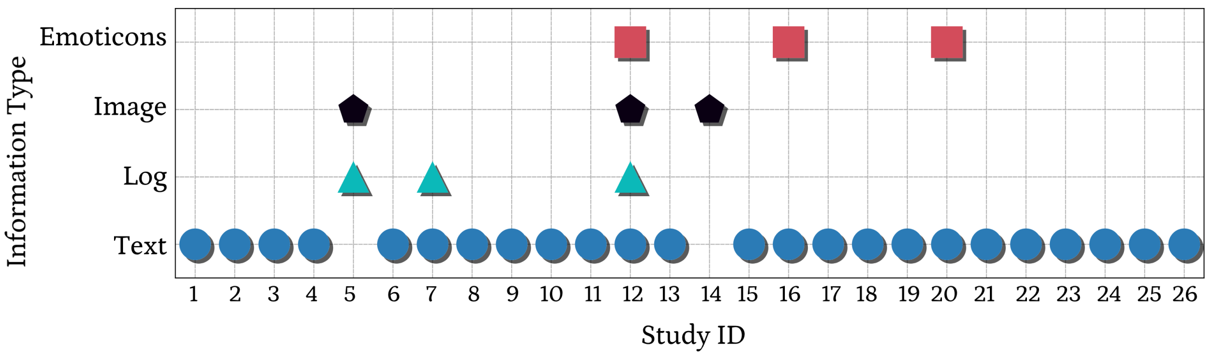

Figure 7 – Type of information available in the social media and used in the studies.

Text was the only media considered by all studies, except for studies number 5 (PARK *et al.*, 2013) and 14 (REECE; DANFORTH, 2017). One of the reasons for this fact is that Twitter is the main social network used, appearing in 10 studies, which is mainly based on text information.

In studies 16 (SHEN *et al.*, 2017) and 20 (POLIGNANO *et al.*, 2017a), the authors used emoticons to improve and provide more meaning to the analysis of feelings regarding the

[3] The Live Journal Platform: <livejournal.com>
[4] The Psycho-Babble Grief: <dr-bob.org/babble/grief/>
[5] The Russian network VKontakte.We: <vk.com>

text. The work of (POLIGNANO *et al.*, 2017a) applied their studies on the Facebook network using NRC Word-Emotion Association Lexicon, WordNet-Affect, as well as Naive Bayes and Multilayer Perceptron classifiers. More recently, (SHEN *et al.*, 2017) proposed a new multimodal depressive dictionary learning model to detect depressed users on Twitter, and compared their solution with Naive Bayes classifier and Multiple Social Networking Learning (MSNL), which was designed by (SONG *et al.*, 2015).

User log information, i.e., the record of users' activities in the network was used by studies 5 (PARK *et al.*, 2013), 7 (SEMENOV *et al.*, 2015), and 12 (WEE *et al.*, 2017a). In the work of (PARK *et al.*, 2013), the authors used a Facebook Web Application to collect data from a survey with Facebook users, based on the self-report questionnaires CES-D (STEINFIELD; LAMPE; ELLISON, 2007) and BDI (BECK *et al.*, 1961). They also performed a Face-to-Face interview and applied correlation metrics to verify differences between the manifestation of depression reported by users online and personally. (SEMENOV *et al.*, 2015) considered user attributes as age, gender, number of friends, and structural properties of their egocentric networks and conducted a descriptive statistical analysis. (WEE *et al.*, 2017a) applied quantitative analysis to understand the behavior of users and obtain evidence or indications of depressive behavior. The authors relayed on logging user activity and texts, images, and emoticons. Although all media types were used, no specific algorithm or technique was proposed by them, only quantitative statistical analysis.

As mentioned before, (WEE *et al.*, 2017a) used images in their work, but only relative to the frequency of the use of images in users' posts, not as an analysis feature. On the other hand, study number 14 (REECE; DANFORTH, 2017) explored the use of only images in the process of detecting depression in Instagram posts. The authors obtained 43,950 photos from Instagram users and used color analysis, metadata components, and algorithmic face detection. The authors used Face detection to recognize a human face in photographs and extracted Hue, Saturation, and Value (HSV) features to find pixel-level averages. Their results show that depressive users' posts had HSV values shifted compared with photos posted by healthy individuals.

Concomitantly to the text, in study 1 (CHOUDHURY; COUNTS; HORVITZ, 2013) analyzed users' log information, while studies number 5 and 7 (PARK *et al.*, 2013; SEMENOV *et al.*, 2015) analyzed users' profiles. (CHOUDHURY; COUNTS; HORVITZ, 2013) analyzed users' frequency records in specific activities, including posting frequency, message sending, among others. In (PARK *et al.*, 2013; SEMENOV *et al.*, 2015) the authors analyzed the users' profiles in order to verify demographic features, such as age, number of joined communities, gender, preferences and user behavior in the network.

The considered studies also employed specific metrics or techniques for each media type. Figure 8 (a) presents a word cloud representation, showing the most cited words in the studies. The most recurrent word is "LIWC", which stands for Linguistic Inquiry and Word Count, a text analysis software that computes the degree of use for different words' categories in a wide variety of texts (PENNEBAKER; FRANCIS; BOOTH, 2001). The core of LIWC software is a lexical resource, available in multiple languages such as English and Portuguese (FILHO; PARDO; ALUÍSIO, 2013). The high frequency of LIWC mainly occurred because the text was the most used media in the considered studies, and LIWC was used in several studies (CHOUDHURY; COUNTS; HORVITZ, 2013; CHOUDHURY *et al.*, 2013a; PARK; CONWAY, 2017; NGUYEN *et al.*, 2017; FATIMA *et al.*, 2017). For instance, (SHEN *et al.*, 2017) use LIWC, EMOJI, and the Naïve Bayes classifier to determine the feelings of postings on multiple social networks.

(a) (b)

Figure 8 – Word Cloud representation of (a) the techniques employed in the studies and (b) additional sentiments and mental illnesses recognized in the studies, besides depression.

Methodologies for text analysis and processing have also been employed. One example is “SentiStrenth”, a polarity verification system used in (XU; PHAN; TAN, 2013), alongside an econometric model. (WANG *et al.*, 2013) used several algorithms such as feature extraction methods, Bayesian networks, decision trees and tables of rules. Additionally, in (CHOUDHURY *et al.*, 2013a) they combined the use of LIWC with the lexical analysis package ANEW lexicon (BRADLEY; LANG, 1999) and the Egocentric Social Graph, aimed at verifying activation and dominance. According to the authors, “activation” refers to the physical intensity degree of emotion (for instance, “terrified” is higher in the activation than “scared”). Plus, “dominance” refers to the degree of control in an emotion (for instance, “anger” is dominant, while “fear” is submissive).

Besides the studies focused on the sentiment analysis with LIWC, (NGUYEN *et al.*, 2017) proposed a regularized regression model called Lasso, and (BIRJALI; BENI-HSSANE; ERRITALI, 2017) applied several traditional machine learning models such as Instance-Based Learning (IBL), Sequential Minimal Optimization (SMO), J48 and CART for classification. (KARMEN; HSIUNG; WETTER, 2015) used the Stanford CoreNLP (MANNING *et al.*, 2014) for the lexical sentiment analysis and vocabulary frequency control to implement a grammar-oriented process. (SEMENOV *et al.*, 2015) used a binary logistic regression and a clustering coefficient and (TUNG; LU, 2016) explored ontology, sentiment analysis, terminology, FAQs, Multiple nominal logistic regression, decision trees, and association rules to determine negative terms. Similarly, (CHOMUTARE, 2014) used bag-of-words and multiple traditional classifiers, among Naïve Bayes, Support Vector Machine (SVM) and Decision Trees (DT), to find negative terms.

Other examples of studies that worked with text are: (VEDULA; PARTHASARATHY, 2017a), where the authors employed ego-networks metrics; (LEIVA; FREIRE, 2017) where the authors used VADER Sentiment Analysis (HUTTO; GILBERT, 2014b); and (HASSAN *et al.*, 2017), which employed Support Vector Machine (SVM), Naïve Bayes (NB) e Maximum Entropy (ME) algorithms.

(PARK *et al.*, 2013) considered users' profiles and text information, and apply the Spearman correlation and the Mann-Whitney U test by means of IBM Statistical Package for the Social Sciences (SPSS)[6] software. In (WEE *et al.*, 2017a) the authors used statistic analysis and a Poisson regression method to analyze users' log information.

3.4.4 Sentiments, Emotions and Other Explored Disorders

The selected studies rely on sentiment analysis and emotion recognition to identify depressive disorders. Thus, each work starts from a specific set of these feelings and emotions, aimed at indicating a depressive disorder. The studies also explore other mental disorders and recognize positive sentiments, mainly to allow the comparison to other techniques. Figure 8 (b) shows a word cloud of the sentiments and mental illnesses recognized in the primary studies, besides depression. It is possible to realize that the feelings and mental illnesses found through the analysis of social media are mostly described as symptoms, specifiers, or predecessors of depression, as described in Section 3.2.

(CHOUDHURY; COUNTS; HORVITZ, 2013) found happiness, sadness, and hate as the main emotions, and they were capable of recognizing discomfort, pain, hope, and concern. (CHOUDHURY *et al.*, 2013a) found positive affect (PA), negative affect (NA), activation, and dominance emotions.

(TUNG; LU, 2016) highlighted anorexia, concentration problems, difficulties of memorization, sleep disorders, anxiety, and suicide-related terms in Web postings. (BIRJALI; BENI-HSSANE; ERRITALI, 2017) found symptoms and traces of anorexia, cyberbullying, fear, heartache, insults, loneliness, and punishment. (WEE *et al.*, 2017a) found Neuroticism, which consists of a characteristic of emotional instability when a person tends to experience negative emotions such as anxiety, anger, or even depression. (NGUYEN *et al.*, 2017) found terms that are related to bipolarity disorders, self-mutilation, distress, and suicide.

In works (XU; PHAN; TAN, 2013; WANG *et al.*, 2013; PARK *et al.*, 2013; PARK; CONWAY, 2017; REECE; DANFORTH, 2017; SHEN *et al.*, 2017; LEIVA; FREIRE, 2017; HASSAN *et al.*, 2017; VEDULA; PARTHASARATHY, 2017a; SEABROOK *et al.*, 2018), the authors only considered the polarity of the sentiment or emotion. In (PARK *et al.*, 2013; CHOMUTARE, 2014; KARMEN; HSIUNG; WETTER, 2015; SEMENOV *et al.*, 2015) the authors do not specify sentiments, emotions, and other disorders. (PARK *et al.*, 2013) had the

[6] IBM SPSS: <ibm.com/br-pt/marketplace/spss-statistics/>

support of specialists to manually relate the answers of a questionnaire to the questions of the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV) (American Psychiatric Association and others, 2013). (CHOMUTARE, 2014) analyzed only positive and negative affects, activation and dominance, and (KARMEN; HSIUNG; WETTER, 2015) started from the principle of finding the recurrence of synonyms of the word depression in Psycho-Babble postings.

(VEDULA; PARTHASARATHY, 2017a) found a correlation between insomnia and depression. (FATIMA *et al.*, 2017) found aspects of rejection, frustration, aggravation, as well as being thirsty, scared, listless, lazy, indifferent, sympathetic, touched, surprised, thoughtful, optimistic, and loved. (POLIGNANO *et al.*, 2017a) recognized the Ekman's universal basic emotions (EKMAN, 1993) as happiness, anger, sadness, fear, disgust, and surprise. (OPHIR; ASTERHAN; SCHWARZ, 2017) analyzed the valence of feelings, but also found anxiety and substance abuse. (LACHMAR *et al.*, 2017) found dysfunctional thoughts, lifestyle challenges, social struggles, hiding behind a mask, apathy, and sadness, suicidal thoughts, behaviors, and seeking relief. (CHENG *et al.*, 2017) recognized suicide risk, anxiety, and stress. (JUNG; PARK; SONG, 2017) assessed self-harm, anxiety, change of appetite, sleep, hypersomnia, irritability, self-esteem, lowered libido, pain, bullying, stress, personality, academic stresses, and loneliness. Finally, (PARK; CONWAY, 2018) recognized bipolarity, schizophrenia, loseit, and bodybuilding.

The feelings, emotions, or disorders encountered by the presented studies and shown in Figure 8 (b) are very similar to those indicated as part of a depressive disorder discussed in Section 3.2.

ID	**Social Networks**	**Media**	**Methods**	**Sentiments and Emotions**	**Other Disorders**
1	Twitter	Text	SVM, LIWC	Valence	-
2	Other	Text	SentiStrength, Econometric models	Valence	-
3	Twitter	Text	Man-made rules, feature extraction, Bayesian Networks, J48; Rules Decision Table	Pretty, love, like, happy, good, ugly, sad, depressed, unhappy, bad	
4	Twitter	Text	Egocentric Social Graph, LIWC, ANEW	Positive and negative affect, activation, dominance	-

Table 2 continued from previous page

ID	Social Networks	Media	Methods	Sentiments and Emotions	Other Disorders
5	Facebook	Image, log	Spearman and Mann-Whitney U test, CES-D and BDI survey	Valence	-
6	Other	Text	Bag-of-words; Bigrams, NB, SVM, DT	Valence	Distress, disturbed sleep, low self-confidence, poor concentration or indecisiveness, poor or increased appetite, suicidal, agitation, guilt
7	Other	Log, text	Egocentric networks and binary logistic regression	Valence	-
8	Blogs / Forum	Text	Stanford CoreNLP	Valence	-
9	Blogs / Forum	Text	NLP processing, extraction of negative features	Boredom disgust loathing	Memory difficulties, loss of appetite and energy, sluggishness, mental fatigue, overeating, agitation fainting, forgetfulness, anorexia, sleep disorder, irritability
10	Reddit	Text	LIWC	Valence	Anxiety
11	Twitter	Text	IBL, SMO, J48 and CART	Valence	

Table 2 continued from previous page

ID	Social Networks	Media	Methods	Sentiments and Emotions	Other Disorders
12	Facebook	Emoticon, image, log, text	User frequency analysis, user activity	Valence	Anguish, emotional instability
13	LiveJourn:	Text	LIWC	Valence	Bipolar disorder, self-harm, grief/bereavement, suicide
14	Instagram	Image	Image analysis, Bayesian estimation, RF, valencia filter	Valence	-
15	Other, Twitter	Text	Linguistic Content Analysis, Gradient Boosted Decision Trees	Valence	Insomnia
16	Twitter	Emoticon, text	LIWC, EMOJI, NB, MSNL	Valence	-
17	Reddit	Text	Logistic Regression, SVM, KNN, RF	Valence	-
18	Twitter, Other	Text	SVM, NB, Maximum Entropy	Valence	-
19	LiveJourn:	Text	LIWC, Decision Forests, ANEW	Rejected, frustrated, aggravation, thirsty, scared listless, lazy, indifferent, sympathetic, touched, surprise, thoughtful, optimistic, loved	Anxiety

Table 2 continued from previous page

ID	Social Networks	Media	Methods	Sentiments and Emotions	Other Disorders
20	Facebook	Emoticon, text	NRC Word-Emotion Association Lexicon, WordNet-Affect, NB, MLP	Happiness, anger, sadness, fear, disgust, surprise	-
21	Facebook	Text	Multiple Regression	Valence	Anxiety, substance abuse
22	Twitter	Text	Qualitative content analysis, NCapture	Valence	Dysfunctional thoughts, lifestyle challenges, social struggles, apathy and sadness, suicidal thoughts, seeking relief
23	Other	Text	Survey, LIWC, Logistic Regression, SVM	Valence	Suicide risk, anxiety, stress
24	Blogs/ Forum, Other, Twitter	Text	Ontology, sentiment analysis, FAQs, Multiple Nominal Logistic Regression, DT, Association Rules	Anger, sadness, fear	Self-harm, anxiety, change of appetite, hypersomnia, irritability, self-esteem, lowered libido, pain, bullying, stress, academic stresses, loneliness
25	Facebook, Twitter	Text	LIWC, MoodPrism, Spearman rho, post hoc comparison, Mann-Whitney Utests, SPSS	Valence	-

Table 2 continued from previous page

ID	Social Networks	Media	Methods	Sentiments and Emotions	Other Disorders
26	Reddit	Text	Linear Least Squares Regression, Lexicon diversity	Valence	Bipolar, schizophrenia, loseit, bodybuilding

Table 2 – Summary of the studies in relation to each aspect analyzed in this work.

3.4.5 Identified Patterns

Table 2 presents a summary of the different aspects considered in this paper, namely the social networks, media, methods, sentiments, emotions, and other disorders identified in the primary studies. By observing the distribution of items in the aspects being analyzed in this work, we can identify the recurrence of patterns among the studies. Table 3 shows the most frequent patterns.

We identified Twitter as the most employed social network, appearing in 10 studies. In all cases, the type of media used was text, and in one of the studies the authors combined text with emoticons. Most efforts employed lexical approaches to explore the information gathered from Twitter. This fact is expected since the information consists of textual data. Also, three of the studies explored Machine Learning (ML) algorithms to analyze the data.

When considering Facebook, the studies used text (four times), image, log information, and emoticon (two times each) as the available media. They explored statistical techniques in two works, mainly for dealing with log information; lexical approaches in other two works for the textual information; and finally, ML approaches in the other three works. The unique effort that employed Instagram, authors considered the images as the media. The three works with Reddit, authors focused only on the textual media, employing lexical and ML approaches to explore the data. Finally, eleven works relied on Live Journal, Blogs/Forum, and other social media in their work. All of them used text, in which one of them also explored Log information combined with text to detect valence. There is no pattern on the methods employed to explore the information of these eleven studies. They counted on a mixture of ML and lexical approaches, ontologies, among others.

The “valence” of sentiments and emotions was the focus of 20 studies. Most of them were based on the analysis of the text (17), with image, log information, and emoticon appearing in three other studies. The studies combined image with log, text with log, and text with emotion, two times each. Also, one study combined all available information, text, image, log, and emoticon.

LIWC was the most employed method, appearing in eight studies, in which all of them used text, and one of them combined emoticon with textual information. In six of the studies, the authors focused on detecting valence. LIWC was mainly explored to analyze data from Twitter (four works) and Live Journal (2 works). Facebook and Twitter together, Reddit and other social media were the focus of one study each.

3.5 Challenges and Opportunities

The main objective of this work is to present state-of-the-art studies regarding the identification of depressive disorders in social networks. We considered both the analysis of sentiments and emotions. Despite the advances in this field, the selected studies allowed us to identify existing problems and opportunities for research. In particular, we observed the following **limitations**:

i. Most studies focus only on the analysis of textual information from postings, log activities, or demographic characteristics of the users' profile.

ii. Most studies did not properly explore the associated media, such as images, videos, and emojis.

iii. Most studies did not consider the users' context, i.e. users' history, or look for changes in the users' behavior pattern along time. In fact, the temporal information is often underused.

iv. Regarding postings, the studies did not consider the interaction and reactions from user friends in the social networks, like comments and other demonstrations of positivity/negativity.

vi. The studies *manually* relate the available information to the Diagnostic and Statistical Manual of Mental Disorders (DSM)(American Psychiatric Association and others, 2013).

vii. The studies did not provide the computational solution online and did not make it available for testing with other users in real-time.

The aforementioned limitations leave open opportunities for multimodal approaches to identify depressive disorders in social network users automatically. The information regarding long-term user behavior is also relevant, and it was not explored in the studies we selected in this review.

Figure 9 shows a high-level pipeline we envision for future approaches focused on the recognition of depression in social networks. Accordingly, the analysis of the data obtained by particular users along time could lead to accurate results, regarding the users' behavior

Antecedent	**Consequent**
Twitter [10] ⇒	Text [10] Text + Emoticon [1] Lexical approaches [7] ML approaches [3]
Facebook [7] ⇒	Text [4] Image [2] Log [2] Emoticon [2] Statistical Approaches [2] Lexical approaches [2] ML approaches [3]
Instagram [1] ⇒	Image [1]
Reddit [3] ⇒	Text [3] Lexical approaches [2] ML approaches [2]
LiveJournal + Blogs/Forum [11] + Others ⇒	Text [11] Log + Text [1] Diverse methods (ML, lexical approaches, ontology, etc.)[11]
Valence [20] ⇒	Text [17] Image [3] Log [3] Emoticon [2] Image + Log [2] Text + Log [2] Text + Emoticon [2] Text + Image + Log + Emoticon [1]
LIWC [8] ⇒	Text [8] Emoticon + Text [1] Valence [6] Twitter [4] LiveJournal [2] Facebook + Twitter [1] Reddit [1] Other (social media) [1]

Table 3 – Patterns identified in the different aspects considered regarding the primary studies.

and the associated temporal information. For instance, it could allow us to take advantage of using frequent patterns mining algorithms to extract relevant information, also relating them to the Diagnostic and Statistical Manual of Mental Disorders (DSM-V)(American Psychiatric Association and others, 2013), and allowing real-time analysis.

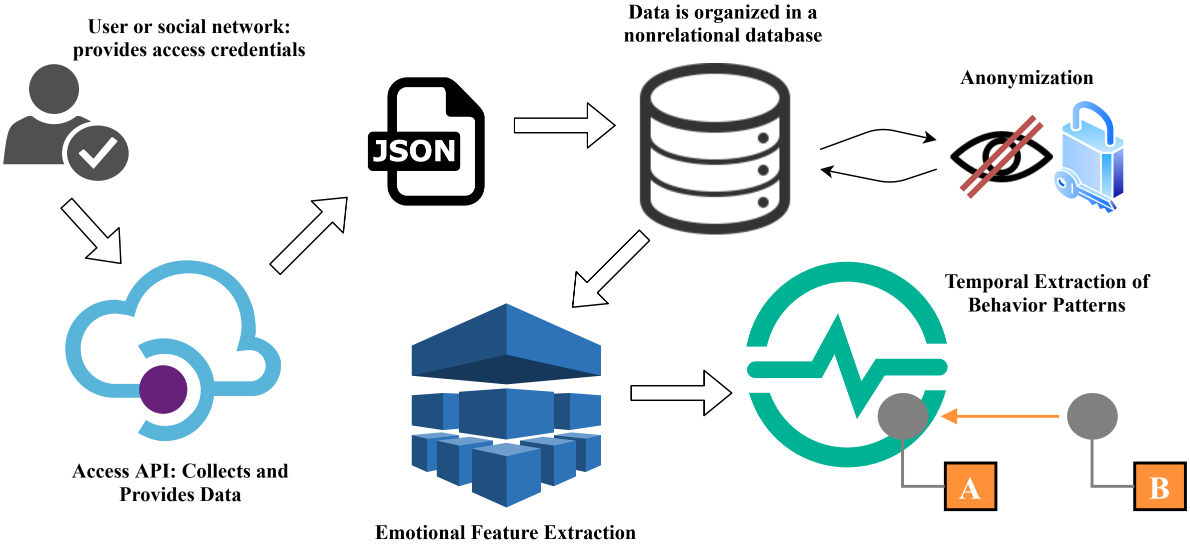

Figure 9 – High-level pipeline for data acquisition from social networks, data storing and organization, anonymization, feature extraction, and finally, the recognition of depressive behavior patterns considering multi-modality and temporal approaches.

Given that the gaps pointed out make it challenging to analyze human depressive behavior, the proposed pipeline (Figure 9) goes from collecting and storing data, through multi-modal extraction of emotional characteristics on social media, to temporal recognition of frequent patterns of depressive behavior.

Another gap that we were able to identify in the state-of-the-art studies is the lack of analysis of the interaction of friends in the social network. The described studies focus on the user data only, without considering the information provided by comments, likes, and other interactions of its connections in the network. Also, we hypothesize that the combination of different types of information, such as text, images, videos, and emoticons, has the potential of improving the overall analysis of the users' behavior. Accordingly, such information could lead to more accurate results regarding the detection of depressive disorders in social networks.

The most popular social networks commonly have an Application Programming Interface (API) for sharing data with applications in various contexts. Examples are Facebook Graph API[7], Instagram Basic Display[8], Twitter API[9] and PRAW - Python Reddit API Wrapper[10]. Each network has a different privacy and data sharing policy, but it is usually required to register

[7] https://developers.facebook.com/docs/graph-api
[8] https://developers.facebook.com/docs/instagram-basic-display-api/
[9] https://developer.twitter.com/en/docs
[10] https://praw.readthedocs.io/en/latest/

an application on the platform. Facebook and other branded products (as Instagram) can only collect data with users' permission. The user accesses the external platform, logs in, and decides which data they agree to share. However, in the latest privacy policy, Facebook does not approve applications that are intended for sentiment analysis, making it disadvantageous to the use of Facebook in scientific research. In Twitter and PRAW, the application can access any content but with limited data requests and downloads.

APIs commonly return a single JSON format file. It is interesting to anonymize and store this data in a well-structured way, although this file can be manipulated as the social network returns it. Furthermore, although Generation and Noise Addition techniques are the most widely used to ensure privacy, in our context, we could lose information that is relevant to pattern recognition, given that user context is an important parameter. A straightforward solution would be to replace the unique user identifier (ID) with a unique hash and randomize them. A more sophisticated solution to ensure data privacy would be the use of Blockchain technologies (ZHANG; XUE; LIU, 2019). With Blockchain, it is possible to keep track of the researcher who manipulated the data.

In the context of sentiment analysis and multimedia information, the use of a non-relational database such as MongoDB[11] may bring better computational performance, reduce costs due to the use of efficient and staggered architectures rather than a monolithic one. Also, non relacional databases allow developers to execute queries without the need of navigating through the SQL data architecture. Besides that, multimedia recovery can be quick and easy.

After storing and anonymizing the data, emotional features can be extracted. As seen in Figure 10, a social network post may provide different types of media. A post contains the user identifier (Username) and may contain text, an image as well as inside information. In this case, insider information refers to the content that we may or may not have in a post, such as comments or reactions (emoticons). Such insider information can significantly contribute to the process of extracting emotional features, as the user's network of friends can react to the post indicating the polarity, emotion, or feeling involved. An example is the study (GIUNTINI *et al.*, 2019), which evaluated the expression of basic emotions (EKMAN, 1993) through Facebook reactions. Thus, with the multimedia extraction of the different media involved in each post, and if privileged information is provided, this can be used to ensure the accuracy of the emotional features.

Finally, emotional features can be analyzed over time to extract and evaluate the evolution of frequent behavior patterns. Therefore, approaches such as Association Rules (e.g. Apriori and Fp-Growth algorithms), Classification (Instance-Based Learners kNN, SVM, Decision Trees and Naïve Bayes), Clustering (e.g., k-Means and Expectation-Maximization (EM) algorithms), Temporal Patterns of Motifs extracted from time series, and temporal patterns (e.g. Allen's Interval Algebra and LSTM) can be explored and combined. However, it is worth noting that the

[11] https://www.mongodb.com/

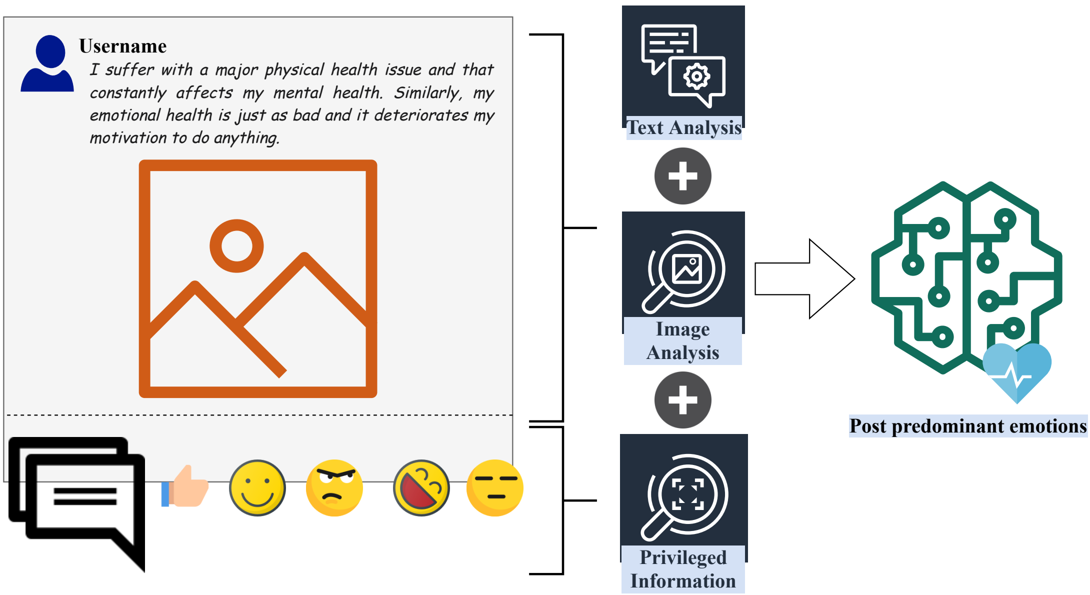

Figure 10 – Multimodal extraction of predominant emotional features of the post.

most significant difficulties of exploring temporality in social networks is the fact that there is no regularity in the frequency of users' posts.

Traditionally, mental health professionals have used clinical examination techniques based on information provided by self-report of emotional, behavioral, and cognitive dimensions (e.g., questionnaire, interviews, standard inventories, among others) for the diagnosis and follow-up of their interventions. The thousands of data regularly posted in the social media could be a valuable new source of personal information, that should bring new light to the analysis process.

The evaluation of the available information in big data has shown to be an efficient and effective tool in the study of dimensions of human behavior, particularly for motivational-emotional ones. These data point to the promising direction of the use of social networks as another instrument in the identification process of depressive moods; it could allow quicker and more accurate diagnosis and follow-up.

By working with user-related data, we deal with sensitive information. Provided the proper ethical approval, these new sources of assessment could lead to effective diagnosis and the rapid identification of mood changes. Considering the implications of depression, the efficiency of timely information and consequent decision support for mental health professionals can be a crucial element in the prevention of suicide.

The research roadmap indicates the strengthening of multidisciplinary research, which will hopefully allow, shortly, substantial contributions to health and the computational development of better algorithms. Such efforts will no longer be linked to the analysis of feelings and emotions in social networking posts, which is currently not used in the medical practice, only in virtual environments. The main goal of future works will be the employment of actual recognition of depressive behavior patterns, as well as the identification of social and cultural aspects related to risk factors in a non-virtual environment. In this way, social networks and their media can give special meaning and be used as objects in the area of Psychology. Finally, future studies may further contribute to the construction and evaluation of new public health policies.

3.6 Conclusion

This paper addressed a review of studies on the recognition of depression in social networks. There are techniques that can automatically identify mental health disturbances, considering indicators and symptoms of depressive disorders (American Psychiatric Association and others, 2013). We focused on studies that automatically identify abnormal behavioral patterns in social networks. However, their performance is considered sub-optimal. Such studies employ data mining techniques, sentiment analysis, and recognition of emotions approaches. Reliable models are very important since they can eventually provide early detection of depressive mood disorders. This can be the basis to lead to fast interventions by physicians, thus promoting relevant public health solutions.

We investigated the state-of-the-art of studies on the identification of depressive disorders in social networks, considering sentiment and emotion analysis, and observed the following points in the selected studies:

1. The **most employed social media** resources for the **identification of depressive mood disorders** are text, followed by emoticons, log information, and images.
2. The **most employed social networks** for the **identification of depressive mood disorders** are, respectively Twitter, Facebook, Blogs and Forums, Reddit, Live Journal and Instagram.
3. The **most employed techniques** for the **identification and classification of tasks** are classic off-the-shelf classifiers, as Naive Bayes (NB), Decision Trees (DT), Instance-Based Learning (IBL), Multilayer Perceptron (MLP), and Support-Vector Machines (SVM). In many studies, such approaches were combined with lexicons as NRC Word-Emoticon Association Lexicon, WordNet-Affect, Anew, and Linguistic Inquiry and Word Count (LIWC) software was widely employed in the selected studies for text analysis.

The challenges envisioned from this study include analysis of temporal information obtained from specific users over time, the use of different types of information concomitantly, and the combination of analysis techniques with the Diagnostic and Statistical Manual of Mental Disorders (DSM-V), provided by (American Psychiatric Association and others, 2013). Finally, we present and discuss a high-level pipeline that systematically organizes approaches and techniques to recognize temporal patterns of depressive behaviors in social networks. This pipeline serves as a guide for future works to explore the main steps related to the detection of depressive behavior in social networks.

Acknowledgments

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Ethical Approval

This work has the approval of the Ethics Committee from the School of Arts, Sciences and Humanities (EACH) of the University of São Paulo, Brazil, under register number 88799118.8.0000.5390.

CHAPTER

4

IDENTIFYING EMOTIONAL EXPRESSIONS ON FACEBOOK REACTIONS USING CLUSTERING MECHANISM

Note: This Chapter is a pre-print of (GIUNTINI *et al.*, 2019), entitle "How Do I Feel? Identifying Emotional Expressions on Facebook Reactions Using Clustering Mechanism", and published in IEEE ACCESS Journal. It is available online at:<https://ieeexplore.ieee.org/document/8698755>

- **Abstract:** The recognition of emotions and feelings through computer technology and devices has been widely explored in recent years. Social networks have become a natural environment in which users express their feelings and opinions through social media, and this includes their Facebook reactions. The aim of this study was to investigate whether the emoticons chosen by users in social network news actually express the emotions they wish to express, having as indicative the polarity of the emotions and the six basic emotions. The data collection was carried out following three courses of action: 1) survey of the posts with higher reactions rates of popular news pages; 2) selection of news by a panel of experts to verify its reliability; 3) identification of reactions, polarity and basic emotions flagged by Facebook users for each news item. Finally, an Expectation-Maximization algorithm was deployed to find the relationship between the reactions and the basic emotions signaled. The results made it possible to determine the polarity and the correlation of the reactions with the emotional expressions. This suggests that the use of reactions in feelings analysis algorithms can increase the confidence in determining the emotion that the content reflects and the emotional state of social network users.

- **keywords:** Facebook reactions, emoticons, recognition of emotions, emotional state, sentiment analysis, social media, social networks, clustering.

4.1 Introduction

Social networks, such as Facebook and Twitter, have changed significantly as people live. Thus, it has become a habit to share and record daily life online. The large sharing of data in social networks has allowed the realization of several studies to analyses of human behavior (GREENBLATT; BECERRA; SERAFETINIDES, 1982; KAWACHI; BERKMAN, 2001; HAWN, 2009; MORRIS; TEEVAN; PANOVICH, 2010; GRAJALES *et al.*, 2014). The use of these online communities is due not only to facilitate of access but also to the fact that these social networks have become an environment in which users feel more comfortable to share their particularities such as their ideas, thoughts and opinions. Thus, the fact is that shared content online, such as texts, images, videos, emoticons and other forms of interaction, has become another lens to be considered by mental health professionals, that is, a new interaction environment to be used for the observation of behavior and social interactions. In the context of social interactions, the expressions of emotions have as functions to provide information about how they feel, regulate interaction and establish intimacy (EKMAN; SORENSON; FRIESEN, 1969); thus, people use these expressions to communicate that they feel joyful, sad, angry, and even to understand the reaction of others in different situations (SCHERER, 2005a; EKMAN, 1993). Expressions of emotions are studied by some authors in various countries (SCHERER, 2005a; WIERZBICKA, 1999), and particularly Paul Ekman has devoted himself to the study of recognition of facial expressions as emotion flags (EKMAN, 1993; EKMAN, 1999; EKMAN, 2006). In a survey of research conducted by his group and other researchers in 21 countries (EKMAN, 2006), in which participants were exposed to photos and in the sequence should indicate the perceived emotion, the author showed that there was an extraordinary agreement among photos of facial expressions and perceived emotions, when comparing the results of the studies between these countries. The emotions focused in the studies were anger, disgust, fear, joy, sadness and surprise, then named as basic emotions. The studies led Ekman to conclude that the recognition of basic emotions is similar between different countries and cultures of the world.

Expressing and recognizing emotions is, however, an important skill for social performance (EKMAN; SORENSON; FRIESEN, 1969), and therefore the recognition of emotions in face-to-face interaction is widely studied (EKMAN, 1993; EKMAN, 1999; EKMAN, 2006; SCHERER, 2005a; WIERZBICKA, 1999). However, few studies have shown how much this experience of expressing emotions can actually be transposed into the interactions that occur in social networks (DERKS; BOS; GRUMBKOW, 2008) such as Facebook or Twitter, which are now the most widely used media. There are about 2.07 billion active users of Facebook (STATISTA, 2017), who spend most of the day online, making the virtual environment a rich source of data about what users think and feel (VASHISHT; THAKUR, 2014). In this type of interaction users often adopt the use of emoticons in posts, messages and comments to increase the meaning of these messages and express emotions with symbols without the need to write.

Emoticons are small images or combinations of diacritical symbols, intentionally developed to replace non-verbal components of communication, suggestive of facial expressions (DERKS; BOS; GRUMBKOW, 2008; VASHISHT; THAKUR, 2014).

The frequency and relevance in the use of emoticons have been the subject of analysis in several recent studies: (OLESZKIEWICZ *et al.*, 2017; WEGRZYN-WOLSKA *et al.*, 2016; WANG; CASTANON, 2015; HUANG; YEN; ZHANG, 2008). Researchers have explored the use of emoticons in various areas: addressing mental health problems; reactions to stressful events; preferences for brands or policy choices; and various opinion polls (LUOR *et al.*, 2010; VASHISHT; THAKUR, 2014; GASPAR *et al.*, 2016).

Emoticons are ways of communicating feelings and even adding textual information to a social network (JIBRIL; ABDULLAH, 2013). However, few studies have explored the relationship between emoticons and textual information (HUANG; YEN; ZHANG, 2008; WEGRZYN-WOLSKA *et al.*, 2016), and even fewer to the relationship between emoticons and the expression of feelings or sentiments (WANG; CASTANON, 2015). While it is claimed that emoticons and, most likely, reactions, can be used to express users' emotions, there have still been few studies that investigate whether they actually reflect them.

One way to determine this is by analyzing the polarity of emotions by means of emoticons; that is, to classify sentiments in positive, negative or neutral states. One method adopted by some studies to understand the meaning transmitted by the emoticons, was to connect them with words through a lexical analysis of emotional feelings by means of finite state machines (i.e., by taking account of all the history of textual production by a particular user, from the oldest to the most recent posts). The attribution of the polarity of emotion could be a useful method of classification because it allows a better grasp of how to conduct a sentiment analysis since the specific attribution of each emotion is quite complex; however, the relationship between polarized sentiments or emotions is not always clear.

Facebook has created a set of emoticons called reactions, to enable its users to react to the contents of the network, such as posts and comments. The reactions defined by the network were: *Like, Love, Haha, Wow, Sad and Angry* as Figure 11. This study aimed to investigate the following:

1. ***How*** *these* ***reactions*** *are employed in the* ***classification of polarity*** *(positive, negative and neutral)*?

2. ***How*** *are described the* ***correlation*** *between the* ***reactions*** *used in Facebook (virtual expression of form) and the* ***emotions*** *(forms of expression in a real environment) can* ***express emotions*** *and to be* ***described as basic emotions*** *?*

Paper Outline: The remaining parts of this paper are organized as follows. Section 4.2

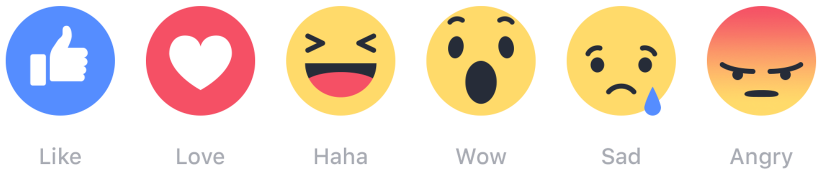


Figure 11 – Facebook reactions

presents the related work about the recognition of emotions using emojis or emoticons. Section 4.3 presents the methodology and materials used. Section 4.4 the results of the analyzes that answer the research questions. Section 4.5 the discussions of the results from the computational and psychological point of view. Finally, in Section 4.6 the final considerations.

4.2 Related Work

This section presents the works most related to this study, that is, that perform the recognition of feelings and emotions in virtual environments, through the use of emoticons, emoji or similar. The works are indexed in the main research bases and are presented briefly in a chronological way in order to show some of the problems addressed, as well as to direct to the research gap. addressed in this work.

Kouloumpis, Wilson and Moore (2011) researched the utility of semantic features for recognizing sentiment in twitter messages. They assessed the convenience of existing lexical assets (utilized in works with e.g., in (YU; HATZIVASSILOGLOU, 2003; KIM; HOVY, 2004)) just as features that catch data about the casual and inventive dialect utilized in micro-blogging. They utilized a hashtag and emojis dataset and utilize an assortment of features for classification tests utilizing n-grams and vocabulary features, acquiring a normal F-measure of 0.65 to 0.68 and an accuracy of 0.74 to 0.75.

In study (LIU; LI; GUO, 2012) was to find the mentality or supposition of the tweets, which is normally figured as a machine learning based content order issue. They utilized two strategies for investigations conclusion: First, physically marked information to prepare completely regulated models; Second, a novel model, called emojis Smoothed moticon Smoothed Language Model (ESLAM) dialect demonstrate to deal with this test. The essential thought was to prepare a dialect display dependent on the physically named information and after that utilization the loud emoji information for smoothing. One aggregate of 3727 tweets was assessed. Around 570 tweets were with valence positive and 654 negatives. 2503 was with unbiased messages. In the wake of expelling the re-tweets or copies and setting the classes to be adjusted, we arbitrarily pick 956 tweets for extremity characterization, including 478 positive tweets and 478 negative ones. For the subjectivity order, we likewise set the classes to be adjusted and haphazardly pick 1948 tweets for assessment, including 974 abstract tweets and 974 targets (nonpartisan) ones. The ESLAM demonstrate accuracy 0.79 to measure the impact of the emoji.

Zhao *et al.* (2012) testing the effectiveness of a framework called MoodLens. In MoodLens, 95 emojis are mapped into four classes of emotions, for example angry, disgusting, joyful and sad, which fill in as the class names of tweets. Therefore, the authors extract over 3.5 million tweets that contain emojis. It shows that in Weibo, there is about 5% of the tweets named by the sentiment emojis. At long last, they acquire 569,229 sad tweets, 290,444 appalling tweets, 2,218,779 joy tweets and 607,715 sad tweets. These tweets could be utilized as an underlying sentiment corpus for Weibo. For each tweet t in T, MoodLens changes over it into a grouping of words wi, where wi is a word and i is its situation in t. In this demo, it is utilized a standard pack of words as the element, set $ft = 0.9, P(cj) = 0.25$ and get a Naive Bayes classifier, its accuracy is 64.3%, the precision is 53.3% and F-measure is 58.3%. The discoveries propose that sentiments varieties are all around caught by MoodLens to viably recognize irregular occasions in China and can be arranged for Naive Bayes, a high classification accuracy.

In (HU *et al.*, 2013) it was proposed an unsupervised sentiment analysis with characters that together seek to represent emotions. For this, it was investigating whether the signals digraphs can potentially help sentiment analysis by providing a unified way to model two main categories of emotional signals, i.e., emotion indication and emotion correlation. The method was based on the comparison of the proposed framework with the state-of-the-art methods on two Twitter datasets and empirically evaluate our proposed framework to gain a deep understanding of the effects of the emotional signal.

Hogenboom *et al.* (2013) analyze how the emoticons convey sentiment. Therefore, they utilized a physically made emoji estimation dictionary so as to enhance the cutting edge vocabulary based assessment grouping strategy. They were assessing the methodology on 2,080 Dutch tweets and gathering messages, which all contain emojis and have been clarified for a conclusion. On this corpus, section level representing estimation inferred by emojis fundamentally enhances slant characterization precision, wherein with 22.02 % right grouping without Emojis and 93.94% of exactness with emojis.

In the (KIRITCHENKO; ZHU; MOHAMMAD, 2014) study it was described the estimation of short casual literary messages, for example, tweets and Short Message Service (SMS) (message-level assignment) and depicted the opinion of a word or an expression inside a message (term-level undertaking). The framework is dependent on a directed factual content characterization approach utilizing an assortment of surface shape, semantic, and notion features. The sentiment features are fundamentally gotten from novel high-inclusion tweet-explicit sentiment vocabularies. These dictionaries it was consequently created from tweets with assumption word hashtags and from tweets with emojis. To enough catch the assumption of words in refuted settings, a different estimation dictionary is created for discredited words. The framework positioned in the (SEMENOV *et al.*, 2015), acquiring an F-score of 69.02 in the message-level undertaking and 88.93 in the term-level undertaking. Post-competition enhancements support the execution to an F-score of 70.45 (message-level assignment) and 89.50 (term-level task). The creators exhibit that the utilization of the naturally produced vocabularies results in execution additions of up to 6.5 absolute rate focuses.

Vashisht and Thakur (2014) looked to portray how emojis can be identified with opinions and are a valuable method for investigating how to discover the extremity of the assessment passed on by the content. They investigated 1,250 statuses and 2,050 remarks on Facebook Internet-based life. The examination demonstrated that the utilization of a limited state machine for emoji inputs was an extremely proficient method for surveying the feeling communicated by the related content. The outcomes validate the way that emojis can be of essential significance when examination sentiments in PC interceded correspondence.

In (NOVAK *et al.*, 2015) study the objective was to investigate if there is emotional content in an emoji and what is the kind of content emotional. For this, it was proposed the main emoticon sentiment vocabulary, called the Emoji Sentiment Ranking. The authors draw a map of the 751 most as often as possible utilized emoticons (Pearson 0.9 and spearman 0.8 correlation). About 4% of the commented-on tweets contained emoticons. The Welch's test-t contrasted tweets with and without emoticon (with the $p - esteem \approx 0$) they can conclude, with high confidence that the tweets with and without emoticons have fundamentally unique assessment implies. Furthermore, the tweets with emoticons are altogether increasingly positive ($mean = +0.365$) than the tweets without emoticons ($mean = +0.106$). The outcomes recommend that tweets with emoticons are all the more sincerely stacked and tweets with emoticons facilitate the prevision of the estimation.

Wang and Castanon (2015) compiled a list of 164 emoticons, which have been used both in previous studies and by Wikipedia, and carried out searches to find out how they were used in a large dataset of collected tweets, over the period of a month, through the Twitter Decahose API. The aim of this study was to describe the use of emojis and their links with Sentiment Analysis, particularly with regard to polarities. The results showed that the emoticons that are most often employed by users, appear to be more reliable predictors of a polarity-feeling. In the case of the emoticons ":)" (allusion to the happy face), ": D" (allusion to the smiling face), ":(" (allusion to the sad face), of 90% of the posts, the agreement about the polarity of feeling attributed to the users was on average 95%. However, they also found that the emoticons which are most often used to express an emotional state of irritation or discomfort, ": /", for example, indicated a negative polarity for about 60% of the participants and neutral for about 20 %. These results suggest that there is not a single relationship between both the emoticon and the polarity of feeling and that the variation could be caused by the specific features of different users.

In (SETTANNI; MARENGO, 2015) was extracted emotions from posts from Facebook users in northern Italy, including text and emojis. Through a Linguistic Inquiry and Word Count (LIWC) and correlation analysis of positive or negative valence, it was possible to recognize some indications of depression, stress and anxiety. In addition, the authors evaluated the behavior of groups by age group, as, for example, it was pointed out that groups of young people tend to express emotions more frequently in their social network posts.

Wegrzyn-Wolska *et al.* (2016) also explored the relationship between emoticons and sentiment expressions on registered tweets. In doing so, the authors compared three pre-processing lexicon-based methods of emoticon-weight on the Twitter-aware tokenizer with a basic Twitter Sentiment Analysis (TSA)TSA of the fifty most widely used emoticons that employ a Naive Bayes (NB). The authors described a group of specific emoticons that can indicate either positive or negative polarity, as well as the following feelings: happiness, surprise, playfulness, affection, acknowledgement, sadness, annoyance, distress, anger and indifference. Their results demonstrated that the use of the emoticon-weight lexicon was a means of upgrading the task of sentiment analysis. It also showed that an emoticon can control the sentiment expression of a tweet, by subduing the emotion of the verbal message. Thus, emoticons may not always belong exclusively to one category of polarity.

In (POLIGNANO *et al.*, 2017b), the authors describe a model that can identify some scenarios of blue feeling, e.g., sadness, loneliness and others depressed feelings. The authors describe the approach adopted to analyze users posts on Social Media Networks (SMNs) by using natural language processing techniques, e.g. emotional labeling of the text and Emoticon-Based Text Annotation for Training Set. The proposed approach is evaluated through an experimental session over a dataset of Facebook posts. In order to quantify the performance of dynamic lexicon for the detection of negative sentences, the results of F1-measure obtained for the classes sadness, fear, anger, and disgust have been averaged. However, the values obtained for dynamic lexicon is 35.00 against 26.65 for Multilayer Perceptron (MLP) and 20.98 for NB, which is a statistically significant difference.

Marengo, Giannotta and Settanni (2017) explore the use of emoji and its relation to personality traits. For this, a Big Five personality assessment questionnaire and a 91-item survey are applied validating the degree of self-identification of the participants with the Apple Color Emoji. Results showed that only 36 emojis are significant in terms of personality traits, such as emotional stability, pleasantness and extroversion. However, the results allow to affirm that the use of emoji allows a free analysis of the language.

In (RODRIGUES *et al.*, 2018a) is presented a database of emojis and emoticons, collected from iOS, Android, Facebook and Emojipedia, built with the objective of evaluating several aspects, such as aesthetic aptness, familiarity, visual complexity, concreteness, excitement and meaning. For this, a research was conducted with participants, where each participant evaluated a set of 20 emojis / emoticons. Finally, the authors present quantitative and descriptive results of the norms obtained, as well as their correlations, examining all datasets.

In (Yang; He; Chen, 2019) solve the problem of noisy labels about the emotional meanings using words and emoticons together. For this, the authors constructed an emotional space as a representation matrix and projected emoticons and words into this emotional space through semantic composition. In addition, a new Emotion-Semantic-Enhanced Convolutional

Neural Network (ECNN) model was created using a MLP as a way to improve performance. Furthermore, by projecting emoticons and words into an emoticon space, it was possible to identify subjectivity, polarity and emotion in microblog environments.

The Table 4 presents a summary of the related works highlighting the main approach, social network, character level used (emoji, emoticon or reaction) and the and the emotions assessed in the study. Through the related works, it is possible to perceive that some of them employ common technical approaches based on sentiment lexicon. Some of them combine lexical analysis with other techniques, such as (WEGRZYN-WOLSKA *et al.*, 2016) that it uses along with Naive Bayes and (VASHISHT; THAKUR, 2014) with finite state machines. In relation to the emotions evaluated, most of the works evaluate only the valence of the feeling, that is, if it is neutral, positive or negative. (ZHAO *et al.*, 2012; WEGRZYN-WOLSKA *et al.*, 2016; Yang; He; Chen, 2019) evaluate some emotions and mood disorders, but only (POLIGNANO *et al.*, 2017b) evaluates Ekman's basic universal emotions using a lexical sentiment analyzer.

Study	**Main Approach**	**Social Network**	**Character level**	**Emotions assessed**
(KOULOUMPIS; WILSON; MOORE, 2011)	Sentiment lexicon	Twitter	Emoji	Valence
(LIU; LI; GUO, 2012)	Probabilistic Language Model	Twitter	Emoji	Valence
(ZHAO *et al.*, 2012)	MoodLens	Twitter	Emoticon	Valence, angry, disgust, joyful, sad
(HU *et al.*, 2013)	Sentiment lexicon	Twitter	Emoji	Valence
(HOGENBOOM *et al.*, 2013)	Sentiment lexicon	Twitter	Emoji	Valence
(KIRITCHENKO; ZHU; MOHAMMAD, 2014)	Sentiment lexicon	Twitter	Emoji	Valence
(VASHISHT; THAKUR, 2014)	Sentiment lexicon and Finite State Machines(FSM)	Facebook	Emoji	Valence
(NOVAK *et al.*, 2015)	Sentiment lexicon	Twitter	Emoji	Valence
(WANG; CASTANON, 2015)	Word2vec and Kmeans	Twitter	Emoji	Valence

Table 4 continued from previous page

Study	**Main Approach**	**Social Network**	**Character level**	**Emotions assessed**
(SETTANNI; MARENGO, 2015)	Linguistic Inquiry and Word Count (LIWC)	Facebook	Emoji	Valence and Anger
(WEGRZYN-WOLSKA *et al.*, 2016)	Sentiment lexicon and Naive Bayes	Twitter	Emoji	Valence, happiness, surprise, sadness, anger and indifference
(POLIGNANO *et al.*, 2017b)	Sentiment lexicon	Facebook	Emoji	Happiness, anger, sadness, fear, disgust, surprise
(MARENGO; GIANNOTTA; SETTANNI, 2017)	Sentiment lexicon and finite state machine	Facebook	Emoticon	Valence
(RODRIGUES *et al.*, 2018a)	Correlation	Facebook and Emojipedia dataset	Emoticon	Valence
(Yang; He; Chen, 2019)	Multilayer Perceptron (MLP)	Twitter	Emoticon	Neutral, happy, sad, disgust

Table 4 – Summary of the related work, including the main approach, social network (source) type of character used and the emotions evaluated in each study.

In contrast to previous studies, the present study addresses the use of a specific set of emoticons called reactions. These reactions have been built by Facebook so that your Facebook users can react sentimentally to posts on the network. For this, through correlations and a clustering algorithm based on estimation and maximization, the study investigates how well these reactions could represent emotion in real life, evaluating the polarities, distribution between emotions and relating to the basic and universal emotions of Ekman (EKMAN, 1993), a form of non-virtual expression. Details of the methodology can be found in the next section.

4.3 Material and methods

The data collection of this study involved the selection of popular news on Facebook, analysis of the reliability of the news by expert judges, a collection of data with Facebook users from a questionnaire elaborated with this news, and correspondence analysis between reactions and basic emotions. Each of the steps will be described below.

4.3.1 Selection of News

Three different researchers selected the news that could be initially used, by surveying the largest news sites posted on their respective Facebook pages, in accordance with the following criteria: 1) they had been posted in the last two days, i.e. to ensure that they were current news; 2) they had more than 500 reactions from the readers, to show that they were news outlets with a wide circulation; 3) they must be free of bias and neutral , i.e. without any religious content, or mention of political and public figures; 4) Six stories were selected to express the six emotions that needed to be evaluated, with the total agreement of the selection group, which meant that a total of thirty-six news items were compiled. The posts describing the news in question should present an image and a phrase that drew attention to what was being portrayed. For example, the image of a burned-out car next to a police car is presented to illustrate the phrase "Carbonized body is found inside car in prime neighborhood of the city". The image of an industrial kitchen containing food on a table is used to illustrate the phrase "Procon finds overdue food in seven famous restaurants". And finally, the image of a child, a couple and another adult portrays the phrase "Marrow donation joins a man and the family of the baby he saved"

4.3.2 Analysis of correspondence between news and basic emotions

The posts were assessed by a panel of seven expert judges so that a set of news items could be compiled that were suitably related to the six emotions proposed in the study by Paul Ekman(EKMAN; SORENSON; FRIESEN, 1969; EKMAN, 1993) for the following analysis. The judges were both professionals and post-graduate students in the field of psychology who are conducting research on how to investigate human emotions. For each news, the judges evaluate separately what was the perceived thrill to watch her. Of the 36 news items initially chosen by the researchers, 24 were selected as the most representative (4 news items related to each emotion), based on the following criteria: 1) a majority of the judges found the same emotion in one news item.; and 2) a majority of the participants found an emotion in the same news item. These criteria resulted in higher percentages of agreement among the judges. The 36 posts were initially presented so that it was possible to discard the less representative posts of each emotion. The choice of 24 posts was based on the estimated amount of at least three items (i.e., three posts) for each factor (i.e each emotion). It is a consensus among researchers that each factor must present at least three items to support the veracity of the items in relation to the factor (PACICO;

Emotion and posts	Judges' concordance (%)
Joy	
(4) Justice decides that parrot raised by the elderly can not be taken by Ibama	71,42%
(10) The world's first water park designed for people with special needs opens in the USA	85,71%
(21) 12 year old boy realizes dream of going to the movies	71,42%
(24) Boy with leukemia receives bone marrow transplant donated by younger brother	85,71%
Sadness	
(12) Carbonized body is found inside a car in the prime neighborhood of São Paulo	100%
(13) I hoped to hold my daughter and now there's nothing more. It is inhumane	85,70%
(26) Working with recycling in polluted air is unique alternative for Syrians	85,71%
(27) Boy loses balance and falls on the slab while bucked kite	71,42%
Anger	
(2) Globo anticipates report of stepmother Isabella Nardoni and promoter will recommend semi-open prison	71,42%
(7) After irritating with crying, stepfather kills with punches child of two years	57,14%
(23) Residents 'fish' in a hole to criticize street abandonment in the interior of SP	57,14%
(28) Woman attacks 12 year old girl after boyfriend gives on teenager	85,71%
Disgust	
(20) Procon finds overdue food at seven famous SP restaurants	42,85%
(30) Girl contracts worm that reached almost 3 meters after eating infected sashimi	28,58%
(16) Fan is beaten in a fight between fans in Curitiba	28,57%
(35) 6 out of 10 Brazilians consider applications as essential as eating	42,85%
Fear	
(15) Thieves surrender security guards and steal almost 400 guns from forum in the great SP	71,42%
(29) Man has killed a coworker because he thinks she would cause him to resign	71,42%
(31) Get rid of canker sores in an instant with this powerful home remedy	28,58%
(32) Horror films that debut in the next few years	57,14%
Surprise	
(33) Macabre: Child's mummy is found in church and hides secret	71,42%
(25) World's oldest gymnast still active at age 91	85,71%
(11) NASA discovers 10 new planets that can harbor life	57,14%
(5) Vatican investigates Brazilian Catholic organization for pact with Satan	100%

Table 5 – News selected according to judges' analysis. From left to right: the news number, the title in English, and the average concordance between the judges. The images, which were presented to the participants can be viewed in GitHub[1]

HUTZ, 2015).The questionnaire, in the present study, consisted of four items (i.e. four posts) for each emotion, and all the postings selected to compose the questionnaire presented moderate to excellent correspondence between the judges (>70%, (LANDIS; KOCH, 1977)), according to criteria described above. The titles of the posts, grouped for each emotion, are shown in Table 5.

4.3.3 General description of the questionnaire

The study used a questionnaire that was prepared with the aid of the Lime Survey tool. The instrument was based on the 24 selected postings as described above, and for each post three questions were asked to be answered by clicking on one of the answer alternatives: 1) What Facebook reaction would you give to the post? The answer could range between the six options of reactions in graphical form, among those of the emotions that the Facebook social

[1] GitHub Link: <https://github.com/ftgiuntini/Reactions-Study>

network makes available; 2) How do you rate this post? The answer could be positive, negative or neutral; 3) Which emotion is most prevalent in this post? The answer could range from "I do not recognize it" to the six basic emotions: joy, sadness, fear, disgust, anger and surprise. In questions 1 and 2 only one answer alternative could be selected for each question. In the third question, the user could choose up to two predominant emotions.

4.3.4 Data collection with users

Users of the Facebook social network were invited to participate in the study by means of a formal invitation made available in the digital media, either personally or on the researchers' social network platform. Before the respondent could be included in the study, he/she had to: 1) be an adult (eighteen years or over); 2) be a user of the social network Facebook; and, 3) have answered the entire questionnaire. Interested participants were invited to respond to the questionnaire described in section 4.3.3 available on the laboratory website and disseminated on digital platforms. The instrument was made available to interested parties for a period of approximately three weeks. When they accessed the research web page, the participants were initially informed of the rationale, purpose, and implications of the study, and given an assurance of confidentiality through a Free and Informed Consent Form. If the participant consented by following the proper acceptance procedures, the questionnaire could be answered immediately. The user's IP address was checked and also there was storage of cookies to ensure only a single response was made by each person ; the user could also stop and return to an earlier reply at any time.

At the end of the questionnaire, the participants were given final guidelines for making contact and thanked for taking part. The information submitted was automatically made available to the researchers and contained the raw data of each participant. The individual results were examined, and two questionnaires were excluded because they did not meet any of the inclusion criteria (both respondents were minors aged 14). Thus, one hundred and forty-seven questionnaires were analyzed. The average rate of agreement of users in relation to the predominant emotion can be checked in Table 6.

4.3.5 Correspondence analysis between reactions, the polarity of feeling, and basic emotions

Considering that it is intended to verify the polarity of feelings and how well Ekman's six basic emotions can be represented by Facebook's Reactions, and starting from the assumptions: (i) that more than one emotion can occur at the same time before an event, such as observing a news post; (ii) that every human can have an interpretation of the news and the reaction, one has a complex problem of separation, taking into account that it is necessary to check how well each emotion can be signed by each class, which in this case are Facebook reactions; (iii) the non-normal distribution of the data collected and selected for final analysis as can be seen by

Emotion and posts	Users' concordance (%)
Joy	
(4) Justice decides that parrot raised by the elderly can not be taken by Ibama	55,10%
(10) The world's first water park designed for people with special needs opens in the USA	97,96%
(21) 12 year old boy realizes dream of going to the movies	95,24%
(24) Boy with leukemia receives bone marrow transplant donated by younger brother	90,48%
Sadness	
(12) Carbonized body is found inside a car in the prime neighborhood of São Paulo	74,83%
(13) I hoped to hold my daughter and now there's nothing more. It is inhumane	85,71%
(26) Working with recycling in polluted air is unique alternative for Syrians	84,35%
(27) Boy loses balance and falls on the slab while bucked kite	78,23%
Anger	
(2) Globo anticipates report of stepmother Isabella Nardoni and promoter will recommend semi-open prison	63,27%
(7) After irritating with crying, stepfather kills with punches child of two years	80,95%
(23) Residents 'fish' in a hole to criticize street abandonment in the interior of SP	44,22%
(28) Woman attacks 12 year old girl after boyfriend gives on teenager	59,89%
Disgust	
(20) Procon finds overdue food at seven famous SP restaurants	57,82%
(30) Girl contracts worm that reached almost 3 meters after eating infected sashimi	78,91%
(16) Fan is beaten in a fight between fans in Curitiba	23,80%
(35) 6 out of 10 Brazilians consider applications as essential as eating	14,29%
Fear	
(15) Thieves surrender security guards and steal almost 400 guns from forum in the great SP	17,00%
(29) Man has killed a coworker because he thinks she would cause him to resign	14,97%
(31) Get rid of canker sores in an instant with this powerful home remedy	20,41%
(32) Horror films that debut in the next few years	7,48%
Surprise	
(33) Macabre: Child's mummy is found in church and hides secret	73,47%
(25) World's oldest gymnast still active at age 91	69,39%
(11) NASA discovers 10 new planets that can harbor life	70,09%
(5) Vatican investigates Brazilian Catholic organization for pact with Satan	51,02%

Table 6 – Average rate of agreement among Facebook users participating in the survey. From left to right: the news number, the title in English, and the average concordance between the users.

histogram in Figure 12. Thereby, the simple Expectation-Maximization (EM) special dataset[2] was used with 3,528 instances (24 news vs 147 responses) to find a matching rate between Ekman's universal emotions and Facebook reactions, as well as to understand the users' feelings when they adopt this feature in the posts. Each instance contains a reaction (like, love, haha, wow, sad, angry), a polarity (positive, negative, neutral) and even two emotions (joy, sandness, anger, fear, disgust, surprise) or 'Not recognize'. The choice of the EM algorithm is based on previous assumptions and for being the most popular approach to solving non-convex problems, with good performance even with missing data.

The EM clustering algorithm basically assigns a probability distribution to each instance to indicate the degree of probability of belonging to one of the clusters (MCLACHLAN; KRISHNAN, 2007). Then, by means of a) a statistical model which generates a X set of

[2] Available in <https://github.com/ftgiuntini/Reactions-Study>

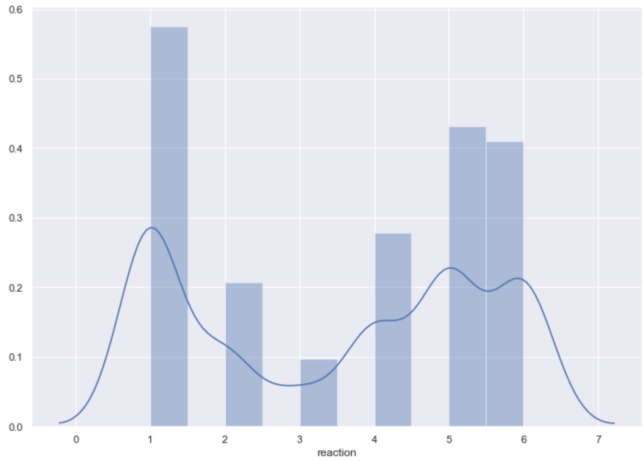


Figure 12 – Histogram of the final dataset in which each instance contains: a reaction, the polarity and even two emotions chosen by the user.

observed data, b) a set of unobserved latent data or missing values Z, and c) a vector of unknown parameters Θ, along with a likelihood function $L(\Theta;X,Z) = p(X,Z \mid \Theta)L(\Theta;X,Z) = p(X,Z \mid \Theta)$, the maximum likelihood estimate (MLE) of the unknown parameters is determined by the marginal likelihood of the observed data.

$$\mathbb{L}(\Theta;X) = p(X \mid \Theta) = \sum_{Z} p(X,Z \mid \Theta) \tag{4.1}$$

For this reason, an initial model (Θ_θ) has been created with arbitrary parameters. The EM phase seeks to find the MLE of the marginal likelihood by iteratively taking the following two steps:

1. **Expectation step (E)**: In this step, the missing data are calculated on the basis of the observed data and current estimates of the model parameters. Thus, the expected log value of the likelihood function is defined in terms of the conditional distribution of Z given X from the current estimate of the $\Theta^{(t)}$ parameters:

$$Q(\Theta \mid \Theta^{(t)} = E_{Z|X,\Theta^{(t)}}[\log L(\Theta;X,Z)] \tag{4.2}$$

2. :**Maximization step (M)**: The 94-likelihood is maximized by making an assumption that the missing data is the known maximization. Thus, the 95-maximiza
-tion parameter is completed as follows:

$$\Theta(t+1) = arg\ max\ Q(\Theta \mid \Theta^{(t)}) \tag{4.3}$$

Finally, the algorithm continues by repeating the EM steps above until it reaches the local maximum. Thus, the cluster number was defined as the number of classes (reactions) and other parameters were initialized with the default values, such as the number of seeds equal to 100 and folds and k-means executions equal to 10; the algorithm continues by repeating the steps EM steps outlined above, until it reaches a local maximum.

4.4 Results

149 questionnaires were completed and 147 instruments that met the criteria were included in the final analysis. The data obtained were transferred to an MYSQL database so that they could be handled more easily. Responses were provided, mostly (85%), by young adults (18 to 35 years) of both sexes. Half of the participants stated that they had subscribed to Facebook for more than 6 years and used it for 2 - 5 hours a day (37%).

Figure 13 shows both the percentage of reaction and the valences assigned to different categories of emotion to the news. From an examination of the results of the reaction attribution, it can be seen that *joy news* received the highest attribution of either the reaction's "like" (42.6%) or "love" category (50.9%), with a strong negative correlation between them (Spearman, r = -0,88, p <0.001). The differences were statistically significant (Friedman, $\chi^2(5)$ = t = 536.15, p <0.001). Although no differences were observed between the reaction "like" and "love" (t = -0.250, p <1,000), the assignments to these reaction were significantly higher than those of other reactions [(love: Haha, t = 1.519, p <0.001; Wow, t = 1.417, p <0.001; sad, t = 1.481; p <0.001, angry; t = 1,500, p <0.001);like: Haha, t = 1.269, p <0.001; Wow, t=1,167, p<0.001; sad, t=1,231, p<0.001; and, angry, t = 1.250, p <0.001)]. Emotionally sad news received mostly sad reaction (74.7%), and no participant attributed "love" to any item of news in this condition. The attribution of sad reaction was significantly higher than all the other responses [Friedman, $\chi^2(5)$ = t = 811.15, p <0.00; like (t = -1.889, p <0.001), love (t = -2.241, p <0.001); Haha (t = -2.231, p <0.001); Wow (t = -1.917, p <0.001); and, angry (t = 2.167, p <0.001)]. News angry received a strong attribution of reaction and angry (49.7%) was significantly higher than the others [Friedman, $\chi^2(5)$ = t = 288.15, p <0.001; like, t =-1,111, p <0.001; love, t = -1.491, p<0.001; Haha, t = -1.065, p <0.001; Wow, t=-1,278, p<0.001; and, Sad, t = -1.000, p <0.001)]. The News classified as fear received the reaction of like in 41.4% of the situations; this value was significantly higher than the other reaction [Friedman, $\chi^2(5)$ = t = 219,15,p<0.001; love (t=1,167, p <0.001); Haha (t=1,185, p <0.001); Wow, (t=0,759, p <0.001); sad (t=0,861 p <0.001); and angry (t=0,472, p <0.020)]. The attributions to disgust news was distributed between Wow (34.3%), angry (22.5%) and sad (21.6%); these reaction values were not statistically different (Wow versus sad: t = 0.352, p < 0.250; Wow vs Angry: t = 0.380, p <0.147; and, Sad vs. Angry: t = -0.28, p <1,000). There was a significant difference when the Wow reaction was compared with all the other ones [Friedman, $\chi^2(5)$ = t = 144,30, p <0.001; like, t = -0.593, p <0.001; love, t = -0.28, p <0.001; and, Haha, t = -0.815, p <0.001]. Moreover, the differences were statistically representative when angry reaction was compared with both love (t=-0,676, p<0.001) and Haha (t=-0,463, p<0,025); and the sad one with either love (t=-0,648, p<0.001)

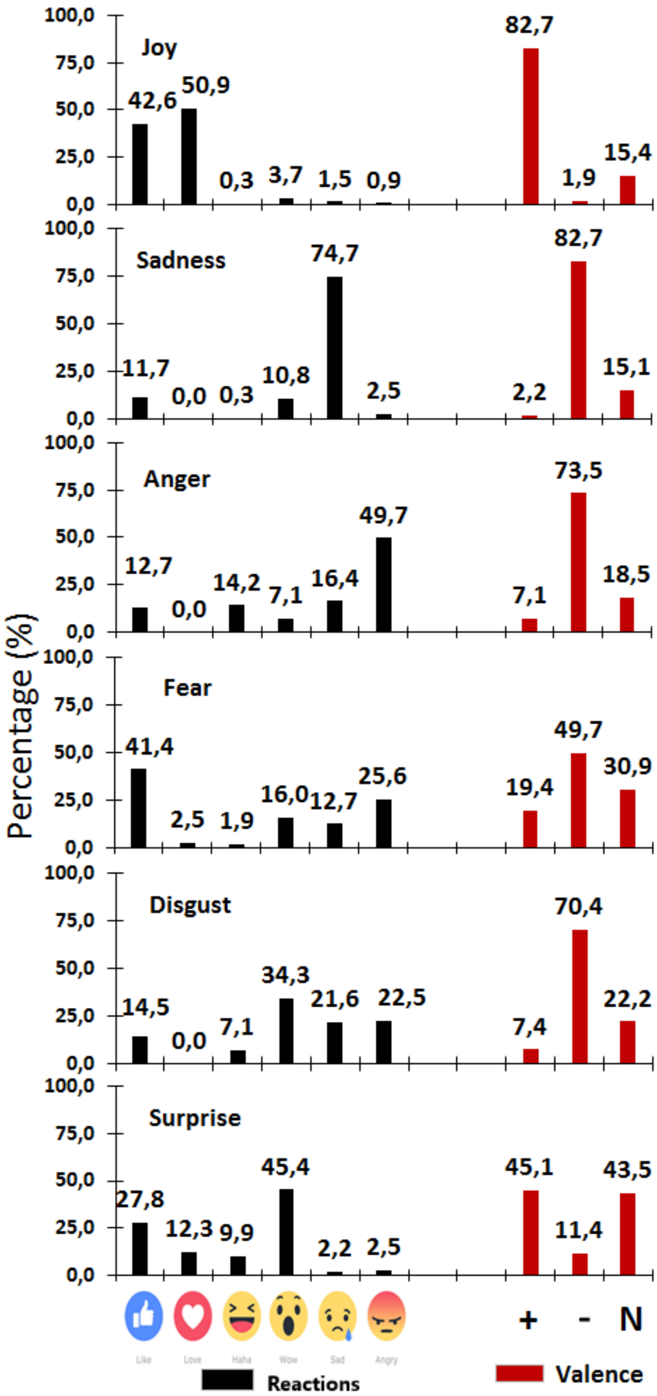


Figure 13 – Percentage of Reaction and valences attributions with regard to the emotion category of the news.

or Haha (t=-0,435, p<0,046). Surprise news received a significantly higher attribution in the reaction Wow (45.4%)[Friedman, $\chi^2(5)$ = t = 276,85, p <0.001; like (t = -0.528, p <0.005), love (t = -0.991, p <0.001; Haha (t = -1.065, p <0.001); sad (t = 1.296, p <0.001), and angry (t= 1.287, p <0.001)]. Thus, the attribution of the reaction seems to have been relatively consistent with the way Elkman's emotion was attributed to the news, although it was not exclusive.

From a scrutiny of the valences attributed to the different categories of news (Figure 13), it is clear that *joy news* generally received a positive valence (82.7%), since it was significantly higher (Friedman, $\chi^2(2)$ = t =364,52 , p<0.001) than the reactions - both negative (1.9%; t=1,213, p<0.001) and neutral (15.4%, t = 1.009, p <0.001); the neutral assignment was also statistically higher than the negative one (t = 0, -204, p <0.029). The reaction love had both a positive correlation with a positive valence (Spearman bivariate correlation, r = 0.43, p <0.001) and a negative one with a neutral valence (r = - 0.40, p <0.001). However, the like reaction showed opposite results: a negative correlation with a positive valence (r = -0.35, p <0.001) and a positive correlation with the neutral one (Spearman bivariate correlation = 0.39, p <0.001). In the Sad news, the differences in valences were also representative (Friedman, $\chi^2(2)$ = t = 363.72, p <0.001), with the negative valency was significantly greater than the positive valence (2.2%; t = -1.208, p <0.001) and the neutral (15.1%, t = 1.014, p <0.001); the neutral valence was statistically higher than the positive one (t = -0.194, p<0.040). In the category of anger, the valences were also significantly different (Friedman, $\chi^2(2)$ = t = 240.07, p <0.001). The negative valence was significantly higher than the positive one (7.1%, t = -0.981, p <0.001) and neutral (18.5%, t = 0.824, p < 0.001); the neutral and positive valences did not show significant differences (t = -0.157, p <0.135). With regard to the news fear, it can be seen that they received a higher negative rating (49.7%, Friedman, $\chi^2(2)$ = t = 45.352, p <0.00). The negative valence was significantly higher than both the positive (19.4%, t = -0.454, p <0.001) and the neutral (30.9%, t = 0.282, p <0.001); the neutral and positive values were not statistically different (t = -0.171, p <0.088). The news with disgusting emotion received a mostly negative valuation (70.4%, Friedman, χ^2 (2) = t = 210.67, p <0.001); this assignment was higher than either the positive valence (t = -0.944, p <0.001) or the neutral ones (t = 0.722, p <0.001). Here it is also apparent that the neutral valence was appreciably greater than the positive valence (t = -0.222, p <0.014). Finally, in the Surprise News, we observed a close distribution between the positive (45.1%) and neutral (43.5%) valences, with no significant difference between either of them (t = 0.023, p <1,000); significant values were observed [Friedman, $\chi^2(2)$ = t=70,13, p<0.001] when the valences were compared - either positive versus negative (t = 0.505, p <0.001) or neutral vs negative (t = -0.481, p <0.0011).

The cluster number was defined as the number of classes (reactions) and other parameters were used to specify the default values, such as the number of seeds equal to 100 and folds and k-means executions equal to 10. For this reason, the distribution of basic emotions is shown in accordance with the clusters in Table 7.

Table 7 – Distribution of Emotions in Clusters by taking account of Facebook Reactions

Attribute	**Clusters**					
	0	**1**	**2**	**3**	**4**	**5**
Distribution	(0.14)	(0.16)	(0.28)	(0.07)	(0.2)	(0.15)
Joy						
mean	0.0017	0	0.0311	0.0054	0.9876	0.0398
std. dev.	0.0257	0.4101	0.1736	0.073	0.1109	0.1955
Sadness						
mean	0.0604	0	0.8725	0.0591	0	0.1053
std. dev.	0.2383	0.445	0.3336	0.2359	0.445	0.3069
Anger						
mean	0.0125	0	0.3494	0.1644	0.0176	0.6284
std. dev.	0.1109	0.0015	0.4768	0.3706	0.1315	0.4832
Disgust						
mean	0	0.0719	0	0.2055	0.0011	0.6262
std. dev.	0.0016	0.2584	0.3246	0.4041	0.012	0.4838
Fear						
mean	0	0.1113	0.1067	0.999	0.0087	0
std. dev.	0.3207	0.3145	0.3088	0.0321	0.093	0.3207
Surprise						
mean	0	1	0.0455	0.0017	0.2357	0.0831
std. dev.	0.4247	0.4247	0.2085	0.0263	0.4244	0.276
Not Recognize						
mean	0.9353	0.0274	0	0.0041	0.007	0
std. dev.	0.2461	0.1632	0.0062	0.0639	0.0832	0.0013

By means of a class evaluation for clusters in the training data, we obtained the assignment of each reaction to the clusters shown in Table 8. Although there was a high recognition rate of basic emotions and a Log likelihood was obtained equal to 4.96, the cross-validation analysis observed in Table 2 shows that some reactions may belong to more than one cluster; that is, it may suggest that there is more than one emotion. As a result, it was pointed out that the maximum aggregation value that the reaction can offer an emotion is up to 56.6%, which is the hit rate obtained by employing the cross-validation system. It should be noted that the reaction "Like" is the one with the fewest representations of both the emotion and polarity of the feeling. In general, it can indicate neutrality and positivity, but despite this, it also appears to be negative.

In cluster 0, a group signed mostly by the like reaction, it is possible to perceive that the respondents do not recognize any emotion (Not recognize) with a rate of 93%, that is, indicating neutrality. The “joy” emotion is mainly represented by Cluster 4 and the reaction “Love” with a rate of 98%, which indicates an extremely positive polarity. However, the reaction “Haha” can represent a set of emotions, since it is distributed in several clusters and the number of instances in which it appears raises serious doubts about the reliability of this emotion. It may indicate a small degree of surprise (Cluster 1) and joy (Cluster 4), but it also appears in “Not Recognize”. Meanwhile, the “Wow” reaction indicates a 100% surprise rate, and this surprise may be positive, negative or be even close to the neutral axis.

When Table 8 was examined more closely, it was found that the “Sad” reaction was the most expressive of the responses, since it represented an 87% rate of sadness and negative polarity. Moreover, the “Angry” reaction also received a high number of responses and its index could represent 62% of the two emotions at the time, with disgust and anger. With regard to the emotion of fear, it does not seem to have a reaction that represents it very well. This is evident from the fact that although it obtained a 99% index in Cluster 3, almost all the reactions participated in this cluster, except the reaction “Love”.

Table 8 – A evaluation of the classes of clusters in the training data

0	**1**	**2**	**3**	**4**	**5**	**Class assigned to cluster**
376	219	35	52	292	62	Like
5	9	0	0	350	1	Love
51	55	7	3	34	23	Haha
17	269	26	62	57	74	Wow
14	77	560	65	3	52	Sad
19	22	156	62	0	467	Angry

Finally, with regard to the polarity distribution between positive, neutral and negative, it can be seen in Figure 14, that the division of the clusters was clear, and that the reactions represent the feelings in question. The emoticon clusters related to “Love” are almost entirely designated as positive polarity. On the other hand, “angry” and “sad” had the most significant concentration of clusters in the negative polarity. The emoticon “like” had clusters distributed in all the polarities.

This suggests that there has been a great advance in the representation of emotion in the area of non-textual information. With regard to Facebook reactions and other studies in the literature, Facebook reactions can add much more information about the emotions and feelings of the user, which was pointed out earlier with regard to the use of emoticons.

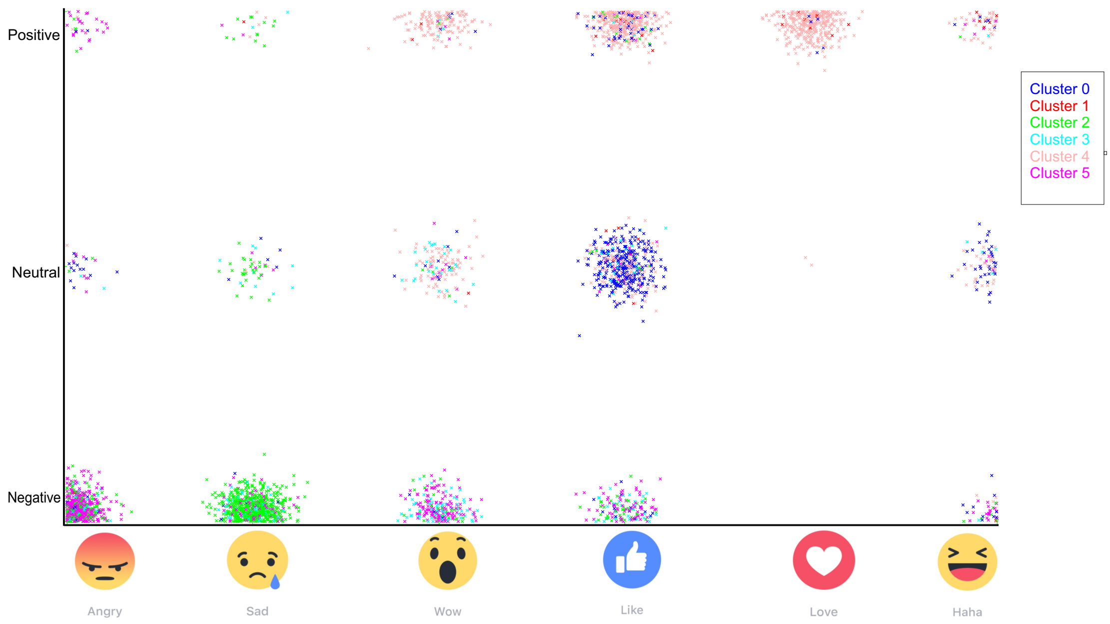


Figure 14 – Distribution of the clusters considering the class reactions and the polarity of the emotions

4.5 Discussion

The fact that there is scientific evidence of a correlation between facial and body expressions and certain emotions is now universally recognized and has been widely documented in the literature (LERNER; KELTNER, 2001; FRIDLUND, 1994; EKMAN, 1993; FRIJDA; MANSTEAD; BEM, 2000; WOLF, 2015). However, there have been few attempts to carry out scientific experiments to investigate this correspondence in the virtual environment - that is to correlate emoticons, sentiment identification and its polarity. The universal expressions of emotions are crucial ways of showing feelings (EKMAN, 1993); as a result, it is possible to maintain that in virtual environments some of these functions the use of reactions. This could be an important development in the area of sentiment analysis. The use of indicators and emoticons for universal emotions should enable methods of emotional analysis to be employed with minimum dependence on verbal semantics. The sample of news items selected for the investigation was relatively complex given the fact that multidimensional features were used to express the information (which usually involved showing pictures and words), rather than only relying on facial information. However, the results showed a consistent attribution, particularly with regard to both emotion and valence, when using different news items; moreover, the division of the clusters was very successful, and the reactions represent the feelings in question very well. This could be an important step in carrying out scientific investigations that can make valid generalizations about emotions, ranging from real to virtual environments, as well as conducting studies of how emotion representation can take place in virtual environments with non-textual information.

Jibril and Abdullah (JIBRIL; ABDULLAH, 2013) point out that the intensification of virtual interactions and expression of emotions through social media is a social phenomenon. This phenomenon may be related to the data found in the present study, as suggested by the time of use of the social network: 51% of the participants use it for 2 to 8 hours a day.

In virtual interactions, emoticons have become the most widely adopted means of expressing emotions (OLESZKIEWICZ *et al.*, 2017). A number of recent studies have been concerned with analyzing them (WEGRZYN-WOLSKA *et al.*, 2016; WANG; CASTANON, 2015; OLESZKIEWICZ *et al.*, 2017; HUANG; YEN; ZHANG, 2008), with the aim of **a)** correlating their use when tackling mental health problems; **b)** assessing reactions to stressful events; **c)** investigating preferences for brands or policy choices; and **d)** conducting several other opinion polls (LUOR *et al.*, 2010; VASHISHT; THAKUR, 2014; GASPAR *et al.*, 2016). The Facebook social network provides particular emoticons called reactions. This new feature can provide us with clues on how to re-establish communication when it is lost in virtual technology, i.e., non-verbal clues (VASHISHT; THAKUR, 2014). It can also enable the kind of emotions that a posting arouses in your reader to be identified. It should be noted that owing to the successful division and distribution of the groups, the emotions were well represented. These distribution data in the attribution of emotions and polarity indicate that there might be a relationship between the emotions felt and the reactions expressed in the virtual environment. This can be illustrated by the following examples: **(1)** as expected, when the participants classified news as "neutral" category, most of them did not recognize any predominant emotional charge in its content ("I do not recognize it" in 74% of the sample); **(2)** some emotions that in natural environments are not socially desirable or enjoyable, are not expressed with a high degree of frequency in virtual environments: the emotional content of the news was classified as disgust 7% of the times and fear 7% of the times.

When some authors investigated the polarity (negative, positive or neutral) of emoticons (WANG; CASTANON, 2015), they found that emotional states of irritation or discomfort were more closely associated with emoticons " :/ ", 60% of participants regarded them as negative; in the present study the "sad" reaction was also closely related (73% of participants) to a negative polarity/classification. Furthermore, in 45% of cases, the "sad" reaction could be correlated with the "sadness" emotion. Thus, it was possible to correlate not only reactions and emotions but also their polarities (neutral, positive and negative).

The "like" reaction can be regarded as a useful phenomenon; in the score for general news (34%) of the items were predominant among the seven choices of possible reactions. (24%), I do not recognize (22%), happiness (16%), I do not recognize (22%), sadness (18%), fear (11%), disgust (10%), anger (17%), as well as positive (29%), negative (34%) and neutral (37%) feelings.

Moreover, if the participants did not recognize any emotion in the news, the "like" reaction was used 64% of the time; which corroborates the broad representativeness of this reaction.

Although the researchers selected the four most representative news stories for each emotion, by following the selection criteria for standardized news (i.e. news items that were circulating in the most representative sites of the news published via Facebook, within the two-day selection period, with at least five hundred reactions that had free and neutral content and accessible language), it was difficult to select news items with a high emotional load of disgust and sadness. This implies there is a trend that is of little value for the social network of Facebook - the linking of information with strong connotations of disgust or fear; or perhaps it suggests that fear and disgust are not socially important to their users.

Some authors have investigated whether there are trends in the use of emoticons and their degree of frequency, by searching for relationships between different features of the users (such as gender and personality) (OLESZKIEWICZ *et al.*, 2017). However, the results suggest that there is a need to carry out additional studies in the area to obtain a more accurate assessment of the influence of user features on the frequency and type of emoticons posted on the Facebook public feeds. By keeping the same variable with regard to "frequency and type of emoticons (reactions, in the present study)", and cross-checking the variable "evaluation of news with a particular emotional load (anger, disgust, fear, joy, sadness and surprise)", it was possible to establish a relationship between the use of reactions and the corresponding emotion generated by the news. News that was considered to be sad, for example (i.e. that was selected and evaluated as sad by the researchers, judges and participants) generally showed "sad" reactions (87%).

In view of the deepening immersion of individuals in virtual environments and the importance of the real representativeness of their emotional content when making use of the vast amount of abundant data generated, it is worth investigating factors that interrelate their personal traits (mental health, emotional reactions, preferences for brands, political inclinations, and information from opinion polls) and the way they have been expressed virtually (i.e. with emoticons), through data collected in virtual environments.

4.6 Conclusion

This study has sought to show how reactions are distributed in the classification of polarity (positive, negative and neutral), and to examine whether they are related to the description of the basic emotions set out by Paul Ekman. This is a way of recognizing if what the user expresses in the virtual environment is something that can represent what he is actually feeling. Other studies may have investigated this factor, but only through establishing a correlation between the reactions posted in virtual environments and the textual analysis by means of **a)** finite state machines **b)** the Naive Bayes classification algorithm, and **c)** classifying the polarity of emotion. Although these methods are widely accepted in the field, they may still fail to recognize the user's emotion, since emoticons (especially those used with less frequency) and textual content may have ambivalent meanings. The way of expressing feelings in a virtual environment and their degree of frequency are also linked to sociodemographic features, and may be influenced by the textual content or the reactions already posted by other users in the public news feed.

This study was carried out in an analogous environment that is free from the influences of the responses of other users, to find out if in fact the chosen reactions were related to the expression of the universal emotions, on the basis of the attribution given by the user himself.

This study provided data that can assist in clarifying whether or not the reactions posted on the public Facebook feeds can be really reliable. Given the fact that emoticons are often used for the expression of feelings in a virtual environment, and that the use of the virtual environment is currently the predominant means of communication, there have been an increasing number of analyses on whether or not reactions are valid descriptions of emotion expression and this has encouraged new studies in the field. Analogous environments need to be more fully analyzed, as well as the correlation between the reactions used in the virtual environment with the expressions of universal emotions.

CHAPTER

5

GROUP ANALYSIS: MODELING AND ASSESSING THE TEMPORAL BEHAVIOR OF EMOTIONAL AND DEPRESSIVE USER INTERACTIONS ON SOCIAL NETWORKS

Note: This Chapter is a pre-print of the (GIUNTINI *et al.*, 2021a), an article published on IEEE ACCESS journal and available in <https://ieeexplore.ieee.org/document/9462934>, June, 2021.

- **Abstract:** The way users interact on social media can indicate their well-being. When depressed, people's feelings tend to be more evident, affecting how users interact and demonstrating their feelings on social media. This paper presents a new approach for the temporal assessment of emotional behavior and interaction among depressed users on social networks. We start by modeling user interactions using complex networks, grouping users through time using the Clauset-Newman-Moore greedy modularity maximization. We evaluate the built networks using metrics such as assortativity, density, clustering, diameter, and shortest path length, closeness, and coverage. Then, we propose EMUS, a method for establishing an emotional user score based on the extraction of emotional features in texts of posts and comments. To extract emotional features, we combine the use of the Empath framework and VADER lexicon. Finally, based on the standard deviation among users, we establish a metric for assessing mood levels. We evaluated users for 33 days, and the results show a sequence of mixed emotional behaviors with high correlations between the number of active users in the network communities, and the form and quality of interactions. The developed approach can be further applied to other database graphs, for different sequential pattern analysis and text-mining contexts.

- **keywords:** affective computing, behavior analysis, complex networks, data mining, de-

pression, emotion recognition, user interaction, sentiment analysis, social media, social networks, text mining, temporal analysis.

5.1 Introduction

Online social networks have become an increasingly natural environment for sharing opinions and feelings, being actually part of people's daily lives. Different social factors and contexts are supported by the use of social networks, such as presented in collaborative works (Li; Huang; Song, 2020), learning (Nkomo; Ndukwe; Daniel, 2020), relationships (LV *et al.*, 2018), and dating (HER; TIMMERMANS, 2020). Today, it is common to first meet someone on a social network and afterwards meet him/her in person (RAMIREZ *et al.*, 2014). Moreover, when a connection first occurs in the real world, it is later consolidated in the virtual environment, even as a sign of mutual approval and interest in maintaining a relationship (SMITH; GALLICANO, 2015).

People have been included social media in their routine, whether for personal or professional use, causing a feeling that life does not have the same meaning without online interactions. The researchers in Affective Computing, an area of science formed by researchers of Computing and Emotions, have explored social media as another lens to model and evaluate emotional behaviors. In Affective Computing, several state-of-the-art technologies and methodologies for various contexts have been developed to (i) understand and model human behavior, predict emotions and mental disorders, as in (Jiang *et al.*, 2017; Kanjo; Kuss; Ang, 2017; Guo *et al.*, 2018; Liu; Jiang, 2019; Zhang, 2020); or (ii) consider emotional aspects in the design of intelligent systems (Zhang *et al.*, 2019; Landowska; Brodny, 2019; Hasan *et al.*, 2020).

The study and recognition of emotions started long ago with Darwin (DARWIN; PRODGER, 1872), way before the computers and integrated systems emerged. In this work (DARWIN; PRODGER, 1872), Darwin investigated children's facial expressions as they interact with their peers, blind or sighted, and persons with disabilities. Darwin founded evidence from some observations that facial expressions corresponded to particular emotions, regardless of each individual's environment. Later, Ekman (EKMAN; SORENSON; FRIESEN, 1969; EKMAN; FRIESEN, 1971) explored the recognition of a set of emotional expressions that could be universally representative and free from cultural bias. Contemporary advances in behavior analysis and new protocols and methodologies have made it possible to assess mood disorders, behavioral, and mental health issues.

Depressive disorders have been a recent research concern in the field of Data Science (CHATTERJEE; GUPTA; GUPTA, 2021), especially after the discovery that data mining approaches can assist in the diagnostic identification and treatment of depression (CHOUDHURY; COUNTS; GAMON, 2012; LIN *et al.*, 2020). In a previous study (GIUNTINI *et al.*, 2020), we provided an extensive discussion about recognizing depressive mood disorders in social networks using machine learning and sentiment analysis. The work presents and discusses the appropriate techniques for specific media, such as text, images, videos, emoticons, and specifics social media platforms.

People with depression (major depressive disorder) commonly experience persistent feelings of sadness, thoughts of worthlessness or guilt, loss of interest in previously pleasurable activities, agitation or psychomotor delay, among other symptoms (World Health Organization and others, 2017). Besides, symptoms can vary from mild to severe, with an incidence of approximately 7% in the United States, with a more significant number of women diagnosed and individuals between 18 and 29 years old (American Psychiatric Association and others, 2013), affecting more than 264 million people worldwide (World Health Organization, 2020).

The Pan American Health Organization (PAHO) (Pan American Health Organization, 2021) informs that a large proportion of depressed people do not receive adequate diagnosis and treatments, and many do not seek health services for this reason. In contrast, social media is accessed by people with different behavioral characteristics, including people with depressive disorders, and has become a rich source of health information (FARPOUR; HABIBI; OWJI, 2017; CHATTERJEE; GUPTA; GUPTA, 2021; GIUNTINI *et al.*, 2020).

Many people experiencing varying degrees of suffering take advantage of virtual platforms to share feelings with others, relate, receive social support, and express their emotional state, especially feelings of helplessness and insecurity (CHOUDHURY; COUNTS; GAMON, 2012). Choundhury *et al.* (CHOUDHURY; COUNTS; GAMON, 2012) followed user's posts on Twitter using the crowd-sourcing methodology. They identified behavior patterns (negative affect, reduced active participation, highly clustered ego networks, occupational activities, relationship concerns, drug treatment, and expressions with religious content) of people who were diagnosed with depression. In (VEDULA; PARTHASARATHY, 2017b), Vedula *et al.* observed the same behavioral patterns and the predominance of nighttime activities on the network, characteristic linguistic styles (*e.g.*, use of self-centered pronouns), and little or no exchange of influence between depressed users and their egocentric network over time. The results indicated that a polarity of negative feelings could be established among depressed users and intense proximity between users with similar problems.

The structural position of users on a social network, and their transitivity (if their friends are friends with each other), and centrality (whether they are located in the center or at the edge of the network), can influence the development of characteristics and behaviors among them (ROSENQUIST; FOWLER; CHRISTAKIS, 2011). Rosenquist *et al.* (ROSENQUIST; FOWLER; CHRISTAKIS, 2011) shows a probability of 93% of a user being depressed if they are directly connected to a depressed person (a friend on social media). Similarly, there is a probability of 43% that a user is depressed if there are two degrees of separation between them (friend of a friend). The probability decreases to 37% if the connections are with three degrees of separation, *i.e.* it is a friend of a friend of a friend. The study also indicated greater severity of symptoms of depression among those located at the edge of the network and a lower score on the depression scale using the Center for Epidemiological Studies Depression Scale, CES-D (HANN; WINTER; JACOBSEN, 1999) for those centralized in the network.

While social ties can have a salutary effect on individuals' mental health and psychological well-being, they can also compromise their health. Face-to-face emotional support was observed in the study (SHENSA *et al.*, 2020) as a protective factor in the development of depression (effect size, 43%). In contrast, social support established in social networks was associated with an increased risk of developing the disorder (effect size, 20%). Considering the exponential increase of users on social networks in recent years (LIN *et al.*, 2020), evaluating the network structure and its impact on users' mental health has been of interest to several researchers in the area.

The literature has explored how relationships take place on social networks and how to conduct an analysis of feelings regarding individual posts and comments. However, it is understood that, for a health assessment and mood disorders such as depression, it is necessary to observe users' interactions and feelings for a more extended period, instead of a single post as most studies consider. This approach can lead to the assessment of changes in the expression of feelings.

This work aims at assessing how interactions between depressive users occur in the social network environment, as well as their correlation with users' emotional expressions. Thus, we investigated and combined the use of algorithms and metrics of complex networks and the extraction of emotional characteristics from the text using two lexicons. Accordingly, we aim at answering the following research questions:

1. *How does the interaction between depressive users on the social network occur? Are there behavioral and emotional changes over time?*
2. *Is there a correlation between interaction and emotional behavior patterns among depressive users in online social networks?*
3. *Can social networks be a suitable environment for mutual support between depressed users?*

To answer the research questions above, we highlight the following contributions:

- We model and assess the interaction behavior of depressed users on social networks using complex network approaches and evaluation metrics.
- We propose and build a method to extract emotional characteristics and polarity of feelings, which serves as an indication for establishing an emotional score of the user. For this, we explore text-mining, lexical approaches, and a pre-trained neural network model.

- We evaluate the correlation between the characteristics of the interactions and the features of emotional expressions extracted from the posts.

Paper Outline: This paper is organized as follows. Section 5.2 presents the materials and methods, including text-mining, complex networks, analysis of feelings, and the extraction of emotional characteristics from posts. Section 5.3 presents the results. Section 5.4 discusses the results by listing the findings using computational metrics and their contributions to behavior analysis. Finally, Section 5.5 gives the final remarks.

5.2 Materials and methods

In this section, we detail methods and materials used in each stage of the process: data collection and description of users; the modulation of the user's interactions of the social network through complex networks and the detection of communities; the metrics used to assess and respond to specific aspects of the interaction behavior among depressive users; the approaches used to extract topics discussed in the communities and to recognize feelings and emotional characteristics. All steps are detailed in the following subsections.

5.2.1 Data Collection and User Description

The Reddit social network has specific communities and flexible privacy terms for data collection. In contrast, Facebook and Instagram have more restrictive privacy policies regarding user posts' collection. Twitter does not have much personal information (ANGER; KITTL, 2011), such as sharing feelings and emotions, is used mainly by mass communication operators (TVs, radios, business's marketing, and newscasts) or famous people, *e.g.*, politicians, artists, and singers. Accordingly, we developed a data crawler using the official Reddit API[1]

The chosen community is very active on Reddit, having more than 713k members and around 1k online users every day. The forum is where the users post, interact using upvotes and downvotes, and insert comments in a hierarchical structure. Given this study's purpose, which considers a temporal evaluation, the most significant difficulties found were (i) finding users who posted regularly and (ii) remained active for 33 consecutive days or more. According to this restriction, for this study, we select 1,212 frequent users that posted for 33 days, with at least one post every three days.

To assess the temporal evolution of a user's behavior in the groups, our database was divided into ten shifts, which refer to 11-time windows with three days each, a total of 33 days of monitoring. To understand the level of depression in the chosen social media community,

[1] The Reddit API documentation is available in <www.reddit.com/dev/api/> to collect posts from a mutual-support sub-reddit community addressing depression (entitled `r/depression`). In the API, we made a REST requisition, defining the community of interest.

we conducted a survey based on the DSM-5 Level 2—Depression—An Adult questionnaire provided by the World Health Organization. To answer the questionnaire, the user anonymously needed to click on the acceptance term. We asked the users about how they felt 30 days ago, 15 days ago, and in the present moment to observe behavioral and emotional changes. The users selected one item from a set of options (never, rarely, sometimes, often, always) for each expression. The expressions are: (i) I felt worthless; (ii) I felt that I had nothing to look forward to; (iii) I felt helpless; (iv) I felt sad; (v) I felt like a failure; (vi) I felt depressed; (vii) I felt unhappy; (viii) I felt hopeless.

It is worthwhile to mention that the collection process and all the methodology described in this section were automated and followed the protocol approved by our institute's ethics committee, whose registration is provided at the end of this manuscript.

5.2.2 Modeling user interaction using complex networks

In complex networks, the term network describes an object composed of elements and the connections between them. Using a social network as an example, the elements are usually associated with people (users), while the connections can be associated with their friendly relationship. Mathematically, the natural way to model these networks is from the graph theory (BOLLOBÁS, 1998).

A graph or network $G = (V, E)$ is a mathematical structure composed of two finite sets V and E, where V is the set of n vertices (or nodes) and E the set of edges (or connections) of the graph. Each graph vertex is normally identified by an integer ordered value $i = 1, 2, \cdots, n$, while the connection between two nodes i and j are represented by (i, j), *i.e.* $E \subseteq (i, j) \mid i, j \in V$. According to the type of edge allowed, graphs can be classified into directed, non-directed, or mixed (STROGATZ, 2001).

To evaluate the interaction behavior among depressive users, we modeled the interaction of users as a complex network. Figure 15 illustrates the hierarchy and how it is modeled as a network. In the social media context and this study, it is understood as an interaction when a user interacts with another user's post, for example, by commenting on it. Then, given that user X commented on user Y's post, a connection is created between the two users by a directed edge of type $X \rightarrow Y$. As this is a direct interaction (post $\rightarrow$ comment), we assign the maximum weight of 100% for this level of interaction in our modeling. Given that the user Y replies on a comment of user X, a directed edge is created with a weight of 50% (*i.e.* $100/2$) in the form $Y \rightarrow X$. We consider this a direct, but secondary interaction in our modeling (comment $\rightarrow$ reply) since the reply is indirectly connected to the main post. Furthermore, the reply and the main post are connected using an edge in our modeling due to the indirect interaction between users, which receives a weight of 33% (*i.e.* $100/3$). In summary, the edge's total weight is divide by the level located in the post hierarchy.

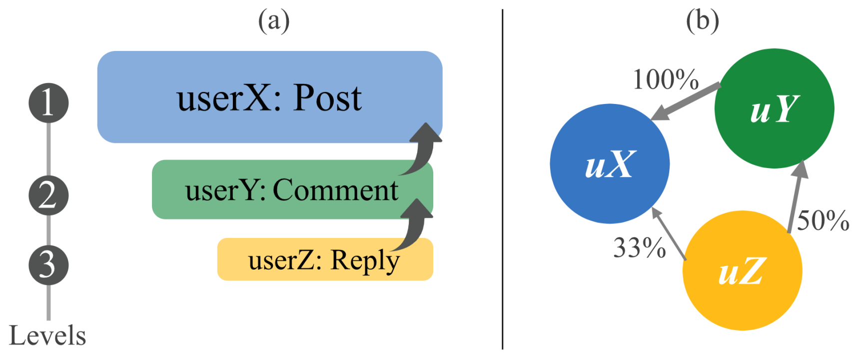


Figure 15 – Proposed modeling for (a) post's hierarchy and (b) interactions' weights.

5.2.3 Assessing the Users' interactions using complex networks' metrics

We applied the Clauset-Newman-Moore greedy modularity maximization method introduced by (CLAUSET; NEWMAN; MOORE, 2004; NEWMAN, 2010; NEWMAN, 2012) to detect communities in the graph. The greedy modularity maximization method starts interactively with each node in its community and joins the pair of communities that have the most potential to increase its modularity until this pair no longer exists. Although the original method does not consider the edges' weight, we adapted the method to consider having an assessment close to the possible social network environment. In this study, we assume that a user has a closer relationship with those who he/she interacts directly with.

The temporal behavior analysis of networks and communities were modeled in 3-day shifts, along 33 days, and we applied the following metrics to evaluate the interaction for all networks in each shift, as well as each community:

- **Assortativity Degree (AD):** Assesses the similarity between nodes in a network (NEWMAN, 2003). The coefficient is the Pearson's correlation between linked nodes, and is typically between -1 and 1, where 1 is considered to have perfectly ordered mixing patterns, and -1 means that the network is totally dissimilar. When AD is positive, nodes tend to connect to other nodes with similar properties within a network. When AD is negative, it indicates nodes' tendency to connect to other nodes with different properties within a network (NEWMAN, 2002). We can understand AD as how depressed users interact with people with similar interaction profiles in our context. It is how practical the network or the community is concerning being a good mutual support environment for depressive user groups.

- **Density (DS)**: Shows how complete the network or community is (NEWMAN, 2012). Considering v is the number of vertices and e is the number of edges in G, the density d of a directed network is defined as:

$$d = \frac{e}{v(v-1)} \tag{5.1}$$

In practice, the Density describes how many potential connections are real connections in a network. A potential connection may or may not exist. For example, user A may know user B. In contrast, the actual connection exists: user A knows or is directly connected to user B. To illustrate, in a family home, the actual connections must be 100%, as everyone knows each other. However, at a train station in a large city, close and authentic connections are expected to be low. This metric answers: how well do depressives know each other, or are they directly or intimately connected?

- **Average Clustering (AC):** Measures the degree to which the nodes of a graph tend to cluster (SARAMÄKI *et al.*, 2007). Evidence suggests that the nodes of most real-world networks, and especially social networks, tend to create cohesive groups characterized by a high density of ties (BARABÁSI; ALBERT; JEONG, 2000). Grouping is a widespread property on social networks, referring to circles of friends where members know each other, thus forming a group on the network. If a node A is connected to B, which in turn finds itself connected to C, there is a high probability that A will also be connected to C (BARABÁSI; ALBERT; JEONG, 2000). In this study, the density indicates: (i) *"how strong the connections between groups of depressive users are?"* and (ii) *"what is the potential of grouping these users?"*

- **Diameter (DM):** The maximum eccentricity, that is, the greatest distance between any pair of vertices. To find the graph's diameter, we find the shortest path between each pair of vertices, and then we verify the greatest path length of the graph (BARABÁSI; ALBERT; JEONG, 2000). In this study, this metric indicates the maximum distance that one user would be from the other on the network.

- **Average Shortest Path Length (SPL):** This metric shows the average number of steps during the shortest path length for all possible pairs of network nodes. It is a measure of the efficiency of information or mass transport in a network (BARABÁSI; ALBERT; JEONG, 2000). In this context, the average number of people a user will have to talk through to contact an unknown person and how easy the discussing topics can flood the network or group.

Further, to analyze the entire network and the quality of detected communities, we counted the number of communities and use the following network metrics:

- **Coverage Community Generation (CCG):** The ratio between the number of intra-community edges to the number of nodes in the network. The plurality of edges is computed if the Graph is a multigraph (FORTUNATO, 2010).

- **Community Generation Performance (CGP):** The ratio of intra-community connections with the total number of possible edges, plus inter-community non-edges (FORTUNATO, 2010).

- **Community Growth Behavior (CGB):** We evaluate the growth of the C_i^j community between two time windows $j-1$ and j as follows. We obtain the absolute number of users present in a given community in the first $|C_i^{j-1}|$ and second $|C_i^j|$ windows. The index calculation is introduced by (SALVE; GUIDI; MICHIENZI, 2018; GUIDI; MICHIENZI; SALVE, 2020). The equation is defined as follows:

$$\text{GR}(C_i^j) = \frac{|C_i^j|}{|C_i^{J-1}|} - 1 \tag{5.2}$$

- **Temporal Dynamic of Communities using F-Score (TDC-F):** We evaluated the permanence (fidelity) of users in the same C_i community over time using the F-score metric, modeling as follows. Let C_i^j be the set of users in community i and at time j. We model the precision and recall between the $j-1$ and j windows as:

$$\text{Precision}_i^j = \frac{|C_i^{j-1} \cap C_i^j|}{|C_i^j|} \tag{5.3}$$

$$\text{Recall}_i^j = \frac{|C_i^{j-1} \cap C_i^j|}{|C_i^{j-1}|} \tag{5.4}$$

$$\text{F-score}_i^j = \frac{2 * Precision_i^j * Recall_i^j}{Precision_i^j + Recall_i^j} \tag{5.5}$$

5.2.4 Observing users' verbal and emotional behavior

To establish and assess the context and emotional conditions of the users, we propose the Emotional User Score (EMUS) method. EMUS works as follows: For each 3-day shift in time, we model the complex network of user interactions and then calculate the user's emotional score, extract contextual characteristics from the conversations, and identify the most common emotions that each user demonstrates through their posts and comments.

Algorithm 1 receives the user's current score as input, which starts with zero if the user has no previous posts and comments. The algorithm outputs the updated user emotional score, the subjects discussed, and the identified emotions. EMUS starts with each new post or user comment (line 2). Function *estimateNegatives* (line 4) aims at estimating the semantic orientation of negative expressions. For this, we used the VADER lexical analyzer (HUTTO; GILBERT, 2014a). VADER is a dictionary of words annotated by the semantic orientation of the feelings that go from -1 to 1, from negative to positive. In this task, we accumulate the values of the semantic orientation of the negative expressions found in the posts' content. Function *estimatePositives* (line 5) performs the same procedure as before, but accumulates the semantic orientations of positive words and expressions. In line 7, EMUS builds a bag of emotions (`userEmotions`). We use Empath, a lexical analyzer based on a trained neural network with 1.8 billion fiction stories for the recognition of emotions (FAST; CHEN; BERNSTEIN, 2016). From such word embedding, the program generates a vector space that tests word similarity, uses seed concepts to identify and find new terms for each of its classes, and filters its classifications utilizing crowdsourcing (FAST; CHEN; BERNSTEIN, 2016). At this stage, we consider the Empath categories of emotions (positive and negative emotion) validated by humans and information about the context in which the emotion is present, such as work, studies, addictions, and pain.

The *userScore* is calculated based on the accumulation of polarities over the user's timeline. For example, if the user posts something positive with valence +55, and later something negative with valence -30, the *userScore* of the user is +25. This calculation is performed at line 9 of Algorithm 1, where the user score is updated.

Algorithm 1 – The EMUS method

```
    Input: userScore, userPosts, userComments
    Output: userScore, userEmotions
 1: Initialization
 2: for each new post or comment do
 3:     Identify positive and negative emotions
 4:     sNeg ← estimateNegatives(userPosts, userComments)
 5:     sPos ← estimatePositives(userPosts, userComments)
 6:     Compose bag of user emotions
 7:     userEmotions ← getEmotions(userPosts,userComments)
 8: end for
 9: userScore ← sNeg + sPos                              ▷ Compute user score
10: return(userScore, userEmotions)
```

5.3 Results

5.3.1 Description of active users

Three hundred fifteen users answered the survey, which was available for 15 days in the virtual community analyzed in this study. Out of 315 users, 45% are in the 18-24 age group, 25% in the 12-17 age group, 24% are in the 25-34 age group, 4% are 35-44 years old, 1% are in the 45-54 range, and 1% are in the 55-64 age group. In total, 57.8% of users reported being male, 37.1% female, 3.5% did not report, 0.9% reported being non-binary or gender-fluid. Regarding race, 64% of users informed to be White, 19% Asian Pacific Islander, 8% Hispanic or Latino, 5% Black or African American, 4% other, and only one person informed to be Native American or American Indian.

Regarding their feelings, using the T-Score scale of the PROMIS of depression for adults (level 2) (American Psychiatric Association and others, 2013), as Figure 16 shows, 30 days before answering the survey, 61.30% of the respondents were classified in Severe depression, 35.9% Moderate, 1.3% Mild, and 1.6% None to Slight. Over 15 days before, the results showed 54% in the Severe category, 41.6% in the Moderate category, 2.9% Mild, and 1.6% None to Slight. When they answered the survey about the current feelings, 55.2% were classified as Severe depression, 31.7% Moderate, and 6% None to Slight.

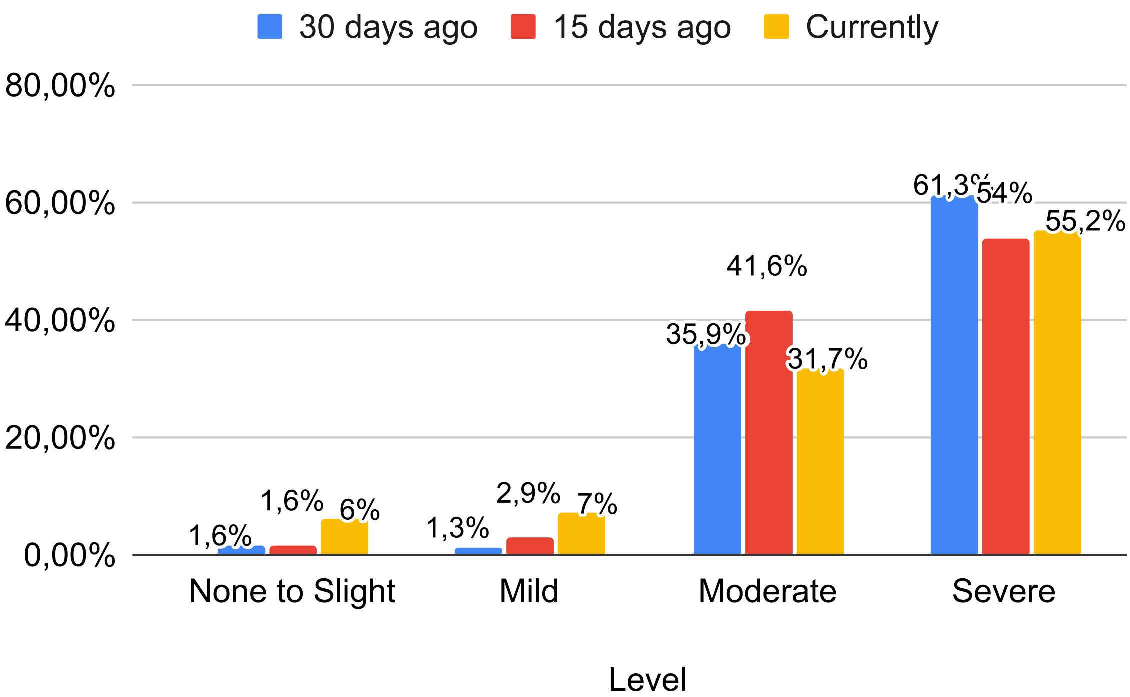


Figure 16 – Depression level users answered the survey about their sentiments for 30 and 15 days ago and currently.

5.3.2 Network Modeling

Figure 17 shows the changes on the modeled network, considering every 3-day shift, from day 1 to day 33, resulting in 11 shifts in time. Every community is highlighted using a different color. Notice that the active users from each community form clusters that are highly interconnected. Also, the number of detected communities changed from a day shift to the other, but seven were modeled at every day shift, which we call the Top-7 Communities. It is worth mentioning that communities are dynamic. They move on the network and change their shape, subjects, and users over time. Also, they can segregate and even cease to exist to the point that new communities emerge. Respecting aspects of privacy and considering that we focus on group analysis in this research, we do not precisely monitor users' paths between communities.

Table 9 shows the metrics extracted from the built networks for everyday shift considered in our modeling. Figure 18 presents the Pearson's correlation matrix among the different metrics from Table 9, where intense colors correspond to high correlation (positive or negative) among

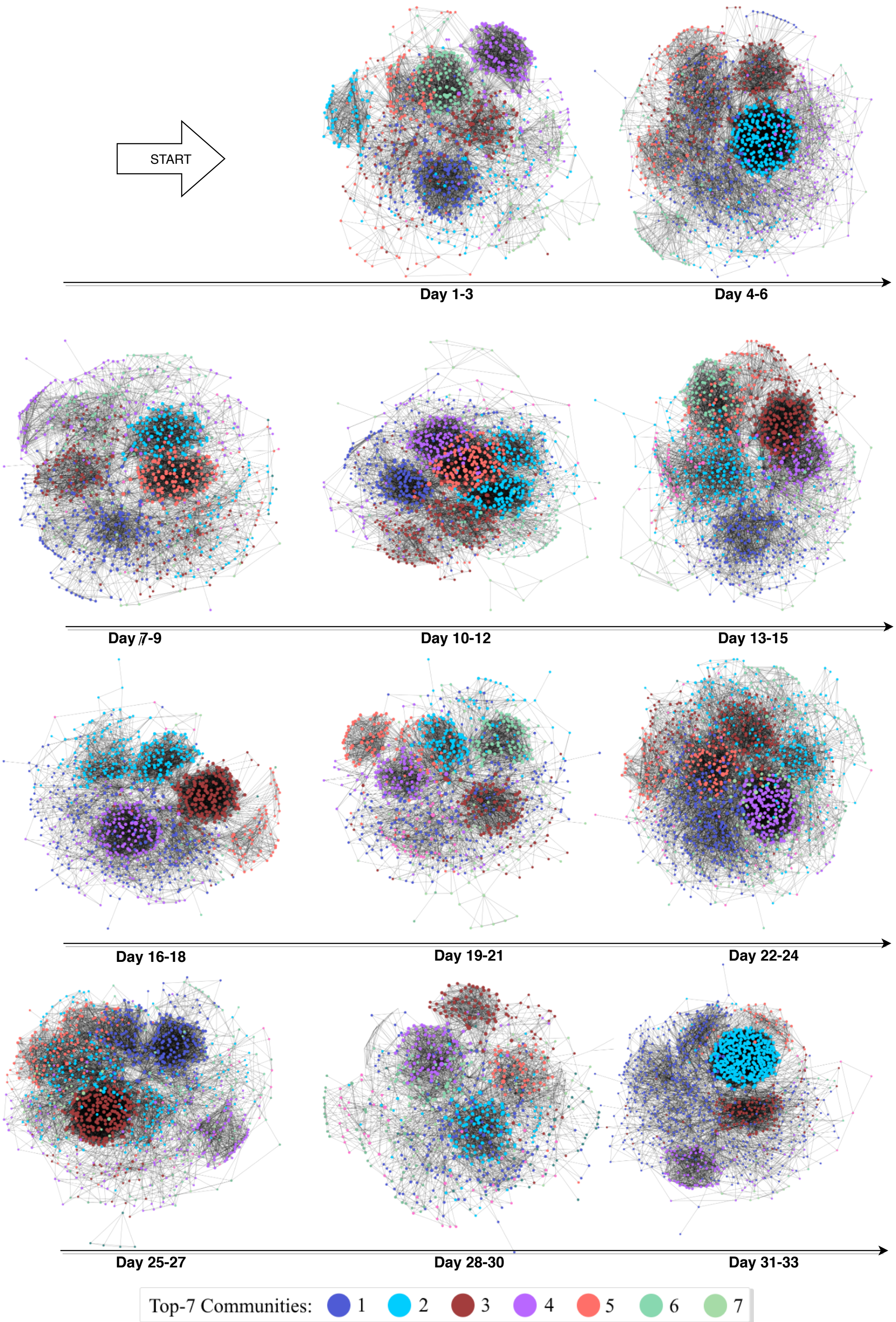
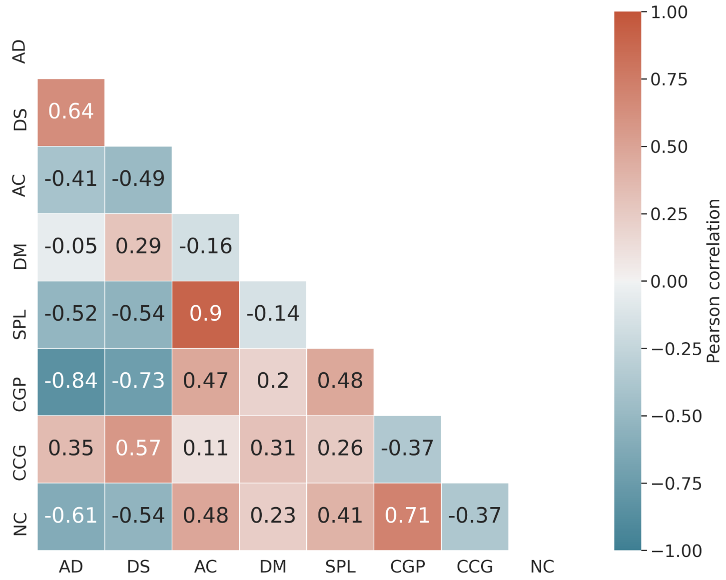


Figure 17 – Complex Network and its communities every 3-day shift.



AD: Assortativity degree; DS: Density; AC: Average clustering; DM: Diameter; SPL: Average Shortest Path Length; CGP: Community Generation Performance; CCG: Coverage of Community Generation; NC: Number of communities.

Figure 18 – Correlation matrix of the network metrics (considering all communities).

the metrics. The Average Shortest Path Length (SPL) values were strongly correlated with the Average Clustering (AC) method, indicating that there is a proximity of users along the interactions on the networks, which in consequence tends to create cohesive groups of users communicating with each other and creating cycles (*e.g.*, User$_a$ interacts with User$_b$, which in turn interacts with User$_c$, which probably interacts with User$_a$). The Community Generation Performance (CGP) and Assortativity Degree (AD) also presented a high correlation. Therefore, the ratio of intra-community connections, considering the number of edges (*i.e.* interactions among active users), was correlated with the connections between users presenting similar properties within the network. The intra-community connections have also shown high correlations with the Number of Communities (NC) and the network Density (DS), which informs how complete the network or community is. These results inform us that the virtual environment of mutual support for depressed users will perform well when the quantity, quality, and form of friendships (connections) are similar. That is, the greater the similarity between users, the better the community. Besides, the denser the network and the more communities, the greater the intra-connections, positively impacting the environment's performance.

Network Metrics	**Day Shift**										
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Assortativity Degree	0.034	0.241	0.091	0.055	0.096	0.13	0.045	0.11	0.15	0.06	0.30
Density	0.014	0.015	0.013	0.015	0.013	0.017	0.011	0.011	0.014	0.012	0.019
Average Clustering	0.33	0.33	0.34	0.31	0.33	0.32	0.33	0.31	0.31	0.36	0.31
Diameter	8	8	8	9	8	8	8	7	9	8	8
Average Shortest Path Length	3.77	3.56	3.77	3.44	3.67	3.51	3.79	3.52	3.61	3.83	3.51
Community Generation Performance	0.87	0.84	0.89	0.88	0.88	0.86	0.87	0.85	0.87	0.89	0.76
Coverage of Community Generation	0.86	0.83	0.85	0.79	0.83	0.84	0.84	0.76	0.85	0.80	0.87
Number of Communities	10	9	9	12	13	11	12	10	12	16	7

Table 9 – Network behavior of depressive user interactions over time. The table shows the network characteristics in different windows (shifts from 0 to 10) of 3 days each, totalizing 33 days of sequential tracking.

5.3.3 Temporal emotion analysis per community

In this section, we describe the temporal emotion analysis over the detected communities of our modeling. We employ the classifications of posts provided by the Empath framework (FAST; CHEN; BERNSTEIN, 2016), identified as positive or negative emotions, and categorize the interactions among active users. Table 10 lists the expressions of emotions in the positive and negative categories. Following, we analyze the temporal changes of emotions identified in posts, considering the top-7 communities of the built network and the classifications provided by Empath, considering the subjects discussed within the communities. We selected only seven communities because it was the highest number of communities present in all-day shifts.

Table 10 – Words from the positive and negative emotions' categories, provided by Empath.

Positive Emotion
happiness, enlighten, better, enthusiasm, pride, joyful, compassion, dearly, forgiving, kindness, bravery, closure, thrill, honestly, triumph, bond, honesty, alive, concern, reunite, joy, surprise, forgiveness, assurance, sympathize, understanding, reason, rejoice, care, faith, great, empathy, certainty, keep, trustworthy, affection, cherish, emotion, love, family, trusting, respect, trust, gratitude, confidence, adoration, friend, happy, overjoyed, determination, reassurance, glad, loved, admiration, wish, accomplishment, optimism, excitement, convince, hope, freedom, feeling, eagerness, willingness, sincere, sincerity, honest, genuine, comfort, elation, thrilled, loyalty, curiosity, unconditionally, proud
Negative Emotion
violent, kill, hell, hate, dying, death, thinking, hated, crying, surprised, hurting, worse, beat, stop, crushed, break, worst, trouble, disappointed, killed, lost, cry, worried, worst_part, bad, stupid, either, die, mean, insane, fucking, scared, hard, dead, beaten, horrible, monster, weak, loose, threatened, punch, killing, blame, reason, so_much_pain, hurts, losing, wanted, pissed, care, scary, accident, fault, guilty, terrible, swear, last_-straw, heartbroken, scare, seeing, drunk, terrified, freaked, raped, frightened, poor_girl, lose, angry, fight, poor_guy, hurt, ashamed, depressed, unthinkable, tortured, crazy, confused, sad, hit, alone, lie, afraid, dying, shocked, angered, sick, badly, pain, react, wrong, mad, upset, fighting, furious

Figure 19 shows the occurrence of positive and negative emotions (and the combination of both, which we call mixed emotions) among the top-5 classifications obtained by Empath, at every 3-day shift, and for the top-7 communities. Empty spots occur when Empath did not classify the community content as containing positive or negative emotions at the corresponding day shift.

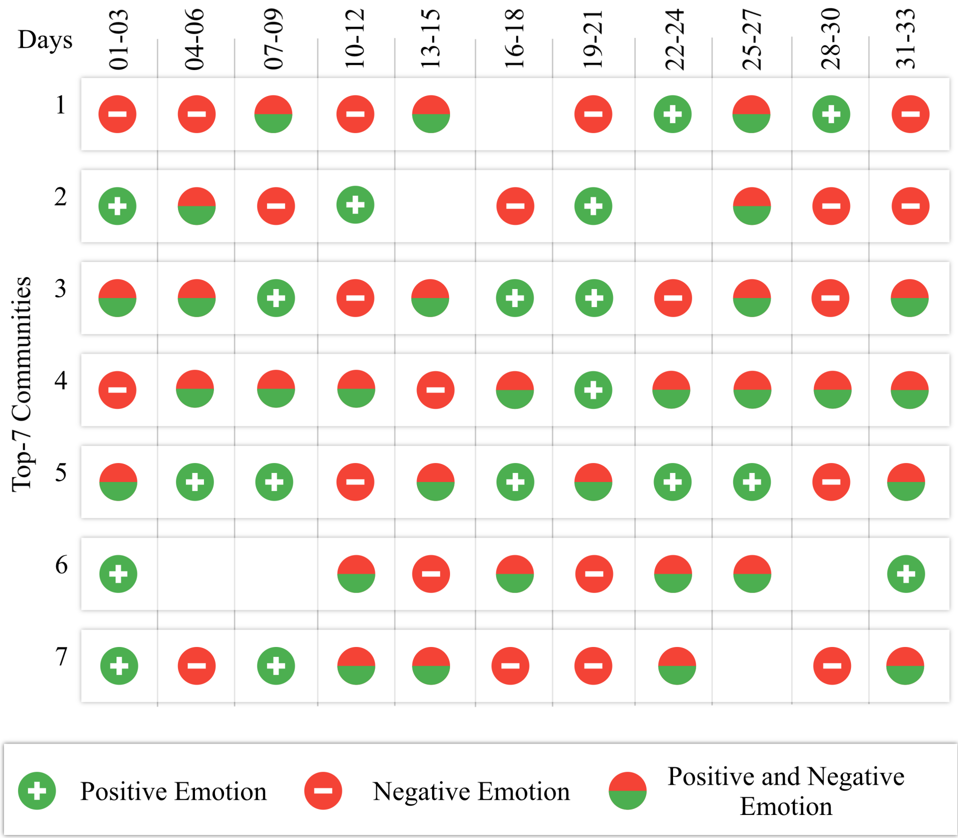


Figure 19 – Identification of positive and negative emotions in the top-7 communities, at every 3-day shift.

Community 1 had the most significant number of engaged users throughout the studied period, presenting an increasing trend: it started with 166 users and finished with 439. During the first five time shifts, the conversations contained mostly negative emotions, for example "shame", "sadness", "pain", "violence", "suffering", and "death" emotions. The approach did not classify the feelings from days 16-18 as positive or negative, but identified mixing emotions: "love", "contentment", "optimism", "pain", and "shame". In the two time shifts classified as positive, the most frequent patterns identified were related to "achievement", "pride", "heroic", and "optimism". Despite the two positive time shifts, the community has focused on posts and replies containing mainly negative emotions, in general. This behavior was similar to the one identified in *Community 4*.

Community 2 started with posts reporting positive emotions related to "love", "friends", "optimism", "affection", interleaving time shifts containing few negative emotions related to, for instance, "death", "suffering", and "violence". The last time shifts of this community contained mainly negative emotions, including "nervousness", "pain", "shame", "violence". *Community 3* also presented an interleaved positive and negative emotion pattern, but with a few distinct classifications: "children", "wedding", "optimism", and "celebration" related to time shifts classified as positive emotions, and "contentment", "pain", "masculine", and "communication" related to time shifts classified as negative emotions. Literature data are similar in pointing out that people with depression tend to have more significant negative emotions on social networks (CHEN; WU; FANG, 2013; LEE; GUAJARDO, 2011). However, some studies highlight the ambivalence of emotional expression, resulting from an internal conflict between the desire to express the negative emotions experienced and the fear of expressing them due to consequences, such as rejection, criticism, or humiliation, among others (TRACHSEL *et al.*, 2010; BROCKMEYER *et al.*, 2013). Therefore, depressive people may be able to inhibit negative emotions at various times. Besides, they do not always express negative feelings, as they may have mood swings depending on the severity of the symptoms (LEE; GUAJARDO, 2011), or even express positive emotions when providing words of encouragement to other network users. Another point observed is the influence that one person can have on the other in social network interactions (ROSENQUIST; FOWLER; CHRISTAKIS, 2011). As observed in community 2, people who initially expressed positive emotions may have been impacted by other network users, which started to increase negative emotions until the end of the data collection.

Although interleaving time shifts with positive emotions with two time shifts related to negative emotions, interactions from *Community 5* presented content related with positive emotions mostly. The positive terms classified include “optimism”, “achievement”, “party”, “heroic”, “pride”, “wedding”, “family”, “love”, “celebration” and “friends”. The negative terms include “shame”, “pain”, “violence”, and “suffering”.

The time shifts from *Community 6* presented the majority of negative emotions, except for the first and last time shifts. Interactions among users from this community focused on themes related to “work”, “college”, “economics”, “business”, “occupation”, “cooking”, “eating”, which mostly do not directly relate to emotions. However, the characteristics found in community 6 emphasize the importance of observing the context in which the user is inserted and its potential impact on emotions, especially regarding work and educational contexts. These characteristics may also be related to occupational activities (“work”, “occupation”, “cooking”, “college”), and financial (“economy”, “business”), and may have stood out for being the target of concern in people with depressive symptoms (CHOUDHURY; COUNTS; GAMON, 2012). Further, users from Community 6 also had conversations classified as “nervousness”, “pain”, “achievement”, “pride”, “heroic”, “shame”, and “optimism”.

Finally, *Community 7* was the only one that started with interactions identified as containing positive emotions and finished with predominantly negative emotions. The initial positive emotions relate to the classifications “party”, “celebration”, “optimism”, “optimism”, “love”, and “trust”. On the opposite, the negative emotions mostly related to “shame”, “nervousness”, “work”, “violence”, “pain”, and “sadness”.

Table 11 lists the emotion transitions over the day shifts, considering only positive and negative classifications, for every community. The subjects discussed within the communities were diverse (*e.g.*, family, work, cooking, party). Nevertheless, none of the communities presented a steady emotional pattern (*i.e.* only positive or only negative emotions). This observation characterizes the dynamics between interactions of users identified as depressive in our modeling.

Regarding the Community Growth Behavior defined in Section 4.3, Figure 20 shows the growth community rate over time. It is possible to observe that the average relative growth is 0.97% over the 11-time windows, that is, with no significant variation. Nevertheless, the shift $8 \rightarrow 9$ presents an expressive growth in all communities. Compared to the demonstration of emotions and feelings on days $28 \rightarrow 30$ depicted in Figure 19, the sum of the polarity presents greater negativity among all communities. The drop in the growth rate of the communities (shift 8) is related to the most significant number of positive expressions.

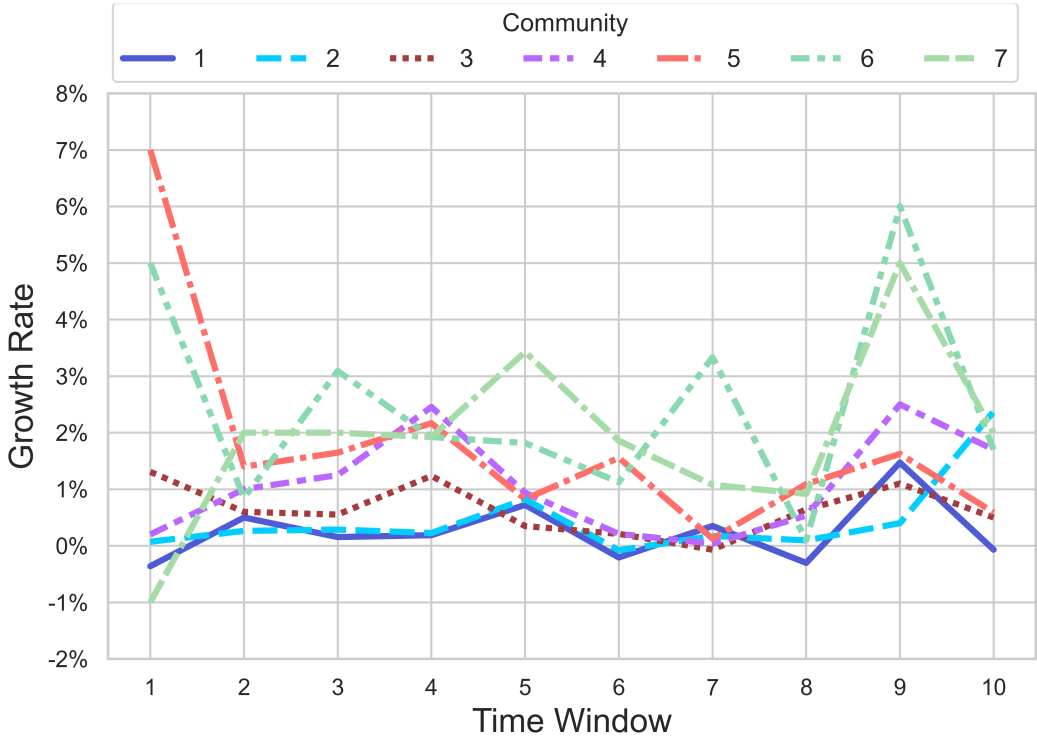


Figure 20 – Communities Growth Evaluation

Concerning the temporal dynamic of communities using F-Score (defined in Section 4.3), Figure 21 shows the percentage of active users who remain in the same community between periods. A low F-score means a high exchange rate between the target community and the rest, while a high F-score indicates that users are part of the same community. Regarding the top-seven communities analyzed, there is a significant exchange of active users between the communities. Regarding users' continuous permanence, community 5 maintained the lowest level of engagement with an F-score below 0.50. Likewise, communities 5 and 6 also had low rates in most periods. In comparison to Figure 21, it is clear that these communities that did not have high engagement mostly show positive feelings in the same period, considering the sum (polarity score). The communities with the most prolonged stay of active users (1, 2, and 6) have a greater expression of feelings of negativity. It is possible to conclude that, in addition to users obtaining more effective communication and closer relationships on the network, the results suggest that they engage more in negative or even depressive topics. This is evident, mainly by community 7, which maintained a medium engagement since it showed mixed feelings. With that, it is possible to conclude that depressives are more engaged in negative topics, and that positive topics cannot engage depressive people in the same way.

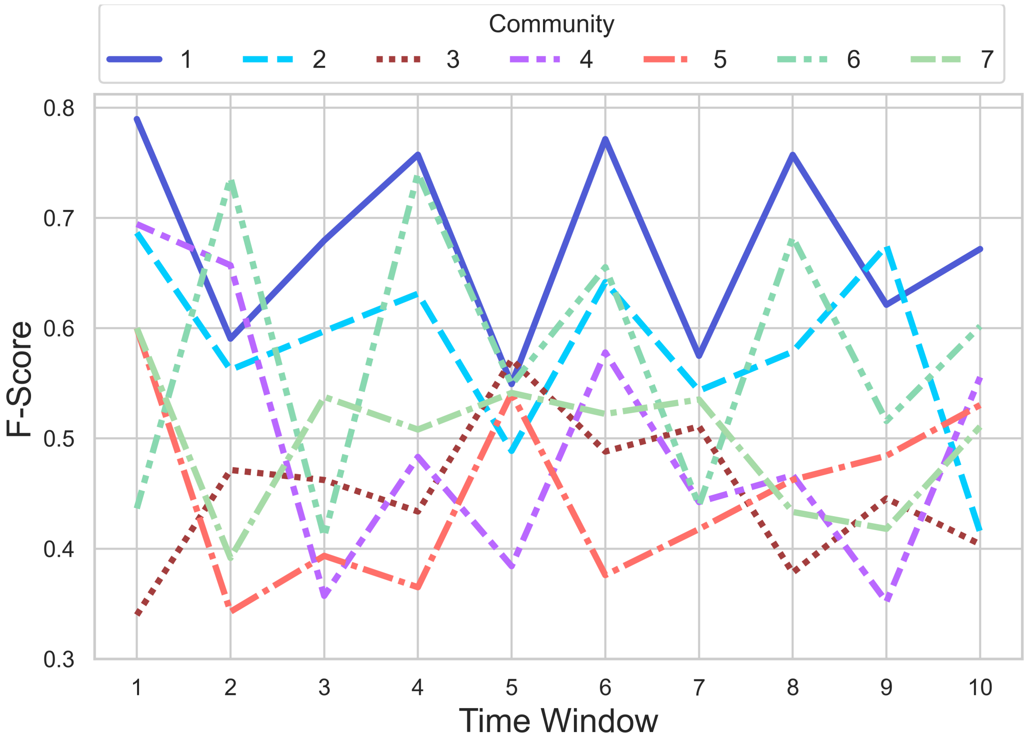


Figure 21 – Dynamic Community Evaluation using F-score

5.3.4 Emotional Users Score

Figure 22 shows the computed emotional score results for users analyzed using our proposed method EMUS, in the windows (shifts) zero, five, and ten. Given users' emotional scores, they were divided into six scales (in different colors), ranging from very depressed to very euphoric. These ranges were established based on the users' standard deviation, where there is a difference of at least 20% between them. On a scale of 0 to 1 (light green color), we define the users as happy for presenting positive feelings within the VADER range, which goes from -1 to 1. In the range of 1 to 2, we defined the user as euphoric (moss green), as he demonstrated much more positive feelings. From 2 (yellow) onward, we define the user with signs of euphoria because the community is among depressives. These users would be showing euphoria and joy far above the average than the environment suggests.

On the more negative side, users from 0 to -1 (bluish-green) were classified as sad for showing negative feelings and expressions but still within the VADER standard. From -1 to -2 (dark green), users were classified as depressive, as they showed above-average negativity. From -3 on (blue), the users are defined as very depressives since they extrapolated the number of negative feelings.

Table 11 – Identified emotion transitions (without considering mixed and absent identifications), and the top classified term at every day shift.

Top-7 Commun.	Emotion transition	Top classification per shift
1	negative → positive → negative	shame; friends; pain; school; friends; love; family; achievement; family; hygiene; shame
2	positive → negative → positive → negative → positive → negative	love; death; speaking; achievement; health; play; optimism; pain; optimism; payment; nervousness
3	positive → negative → positive → negative	optimism; violence; optimism; shame; shame; optimism; party; speaking; pain; shame; pain
4	negative → positive	messaging; shame; speaking; pain; suffering; shame; optimism; violence; pain; speaking; appearance
5	positive → negative → positive → negative	pain; optimism; optimism; home; friends; optimism; communication; achievement; optimism; speaking; friends
6	positive → negative → positive	achievement; work; cooking; hygiene; pain; optimism; pain; trust; phone; nervousness; optimism
7	positive → negative → positive → negative	party; pain; optimism; celebration; optimism; pain; sleep; optimism; pain; sadness; celebration

Observing the User Score results showed in Figure 22, the growth rate in Figure 20 and the dynamic behavior of communities in Figure 21 using F-score, it is possible to note that there is an increased expression on negative emotions, an increase in community rate, and a height exchange of active users between communities in the same shifts.

5.4 Discussion

This study identified a high level of proximity patterns between depressive people who have similar behavior patterns. The most active users are grouped with their peers, and in less active users, the same effect is observed. Perhaps this proximity occurs because it is easier to approach and interact with people whose experience and similarly express themselves, creating greater intimacy.

5.4.1 Takeouts from Existing Works

Our study corroborates with those of other studies (CHOUDHURY; COUNTS; GAMON, 2012; WEE *et al.*, 2017b). In (WEE *et al.*, 2017b)), the authors employed traditional instruments

(CES-D on depression and IPIP NEO-Domain items on neuroticism questionnaires) to measure depression and neuroticism. The authors shared the questions of CES-D and IPIP NEO-Domain via a survey with social media users and compared with the number of posts and comments, *i.e.*, the user frequency activity using statistics (mean, median, frequency, standard deviation). The results demonstrate similar personality patterns among those whose group demonstrate that engagement in activities is related to the users' level of depression and how much-depressed users are inclined to do more broadcast. Likewise, Choudhury *et al.* (CHOUDHURY; COUNTS; GAMON, 2012) applied a survey on MKturk (https://www.mturk.com/) and used the lexicons ANEW and LIWC to extract categories from the text with the users' posts frequency. Unlike the works cited, our computational solution does not directly interact with users by interviews nor questionnaires. Our approach is automatic and combines different complex network metrics to extract emotional categories using EMUS. This automatic approach allows specialists to perform a premature analysis and recognition of depression indications, enabling timely interventions.

Despite the effectiveness in identifying behavioral patterns among depressed users of social networks, our study also pointed out that the social network may not be an adequate environment for developing coping strategies in this population. The observed effects depicted in Figure 22 show that the proximity between peers, due to similar characteristics, promoted an increase in negative feelings (sadness, depression), while positive feelings remained or decreased. This may be because the interaction does not happen between people who have different characteristics, which can hinder the development of learning new behaviors. Although social networks are beneficial to users' mental health, in (ROSEN *et al.*, 2013) the authors identified that greater participation and the more significant number of friends on Facebook were related to less depressive symptoms. The way these relationships are established (types of groupings developed) may significantly impact behavior change. The present study also has raised other relevant questions. For example, if social networks can become an adequate environment for interaction and mental health promotion, would they be sufficient for this task? In (SHENSA *et al.*, 2018) the authors found an increase in depressive symptoms among people who are highly active on social networks and reported having few or not having close friends outside of social networks (face to face). In contrast, people who reported a more significant number of close friends outside the network (face-to-face) indicated fewer depressive symptoms. The interactions established on social networks are useful for identifying patterns of behavior and predicting diagnoses of depression. However, as interactions naturally happen among people with related interests, such interactions do not seem to be useful (or even sufficient) to promote the reduction of depressive symptoms.

5.4.2 Final Considerations and Future Work

In this work, we graphically and quantitatively discussed the temporal interaction of users in social media, focusing on emotions and depression. Our method allows specialists to follow the behavior of a community of interest, analyzing their interaction systematically. The analysis provided in this study also indicated a relationship between the pattern of interaction and emotional responses between users. The interaction is beneficial when there is a high degree of proximity between users when communities are dense and feelings are negative. What has been observed is that depressive users interact only with users who have the same degree of interactions and similar emotional characteristics. Although there are positive feelings, the interaction occurs better when there is a more significant negative feeling. This leads to the reflection that depressive users on social networks tend to get closer to other people who express negative feelings.

5.5 Conclusion

This paper presents an approach to investigate the interaction and emotional behavior among depressed users on social networks. Initially, we modeled users' interaction behavior using algorithms and metrics of complex networks, and we evaluated the structures with their intrinsic metrics. We also developed a method that combines two lexicons to extract emotional and contextual features from users' texts: posts and comments. A crawler was developed, and posts were collected from 1,212 users from a mutual support community about depression on Reddit. Part of the users was also evaluated by a survey with questions of PROMIS of depression level 2 for adults (American Psychiatric Association and others, 2013), which demonstrated that most of them have severe depression.

The results showed a high correlation between interaction and mixed emotional behaviors, varying between positive and negative feelings. However, the expression of negative feelings is much greater and more evident. Regarding the interactions, results suggest that networks are a suitable environment for mutual support when groups are dense and have a high similarity between them in terms of form, performance, and proximity of interactions.

The obtained results suggest that emotional aspects may be closely linked to how users interact and their profile, demonstrating that it is more effective and comfortable to obtain mutual support with friends (connections) closer in the distance and behavior. On the other hand, this draws attention to the difficulties that depressive users have in establishing relationships and engagement with different people, who comment or post about other subjects, demonstrate different emotional expressions and affection, and do not have a degree of similar interaction. In short, depressives prefer to communicate with equals.

In this study, we highlight the following contributions: (i) an approach that takes advantage of complex networks to assess the interaction and emotional behavior in social networks considering the temporal aspects of such interactions; (ii) a method for extracting emotional features and building an emotional user score based on the content of user's posts and comments; (iii) the discovery of ranges of features values that indicate mood disorders; (iv) a correlation analysis between the interaction patterns and the emotional aspects was highlighted in our modeling in the top communities.

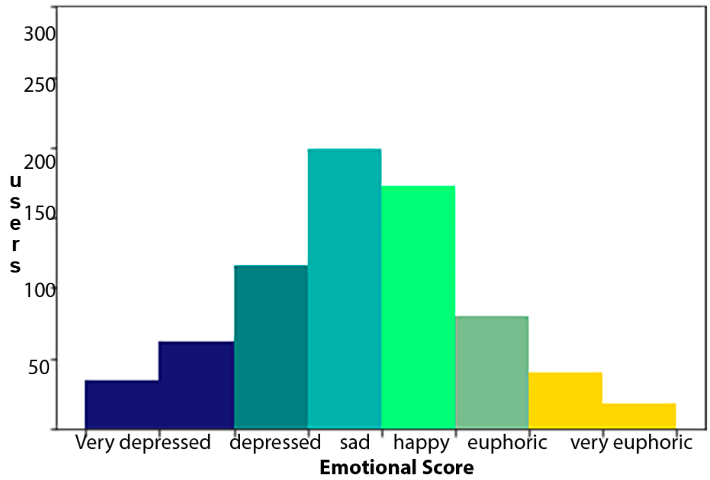
By exploring technologies and general approaches to graphs, temporal analysis, and text-mining, our proposed approach is not limited to the context of data from depressive users on social networks. Therefore, it can be used for other graph-oriented databases that use text as the primary information. In this way, it is possible to explore other contexts and platforms that use texts, such as anxiety in chatbots. As future work, we encourage:

1. Comparing the behavioral patterns found in one community with the behavior of others;
2. Further exploring of the developed approach with other communities of mutual support regarding other diseases, transgender and contexts, such as anxiety, drug addictions, crimes, schizophrenia, among others; and
3. Adapting the approach to other graph-oriented database contexts, such as problem logging on mobile devices and collaboration of computer scientists behavior in code versioning systems.

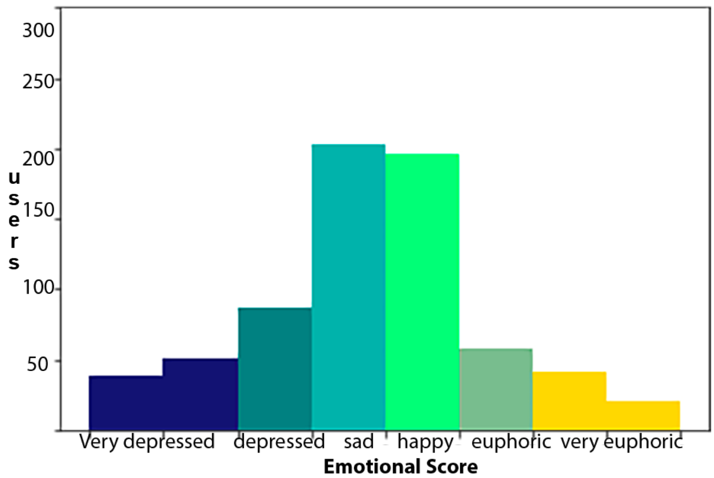
Supporting information

This work has the approval of the Ethics Committee from the School of Arts, Sciences and Humanities (EACH) of the University of São Paulo, Brazil, under register number 88799118.8.0000.5390.

(a) Shift 0 (Day 1-3)



(b) Shift 5 (Day 16-18)



(c) Shift 10 (Day 31-33)

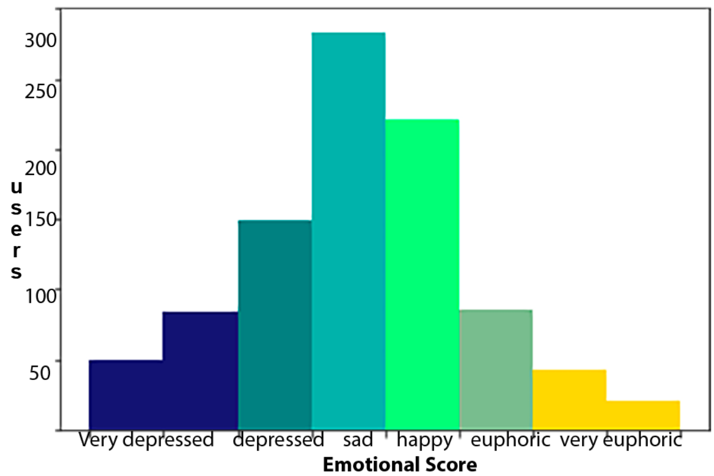


Figure 22 – Histograms of the number of users classified according to their emotional score along time using EMUS.

CHAPTER

6

INDIVIDUAL ANALYSIS: TRACING THE EMOTIONAL ROADMAP OF DEPRESSIVE USERS ON SOCIAL MEDIA THROUGH SEQUENTIAL PATTERN MINING

Note: This Chapter is a pre-print of the (GIUNTINI *et al.*, 2021b), an article published on IEEE ACCESS, v.9, pp. 97621-97635, July, 2021.

- **Abstract:** Depression is one of the most growing public health disorders, generating social and economic problems globally. Intelligent models of affective computing oriented to data from social networks have been developed in recent years to assess human behavior and predict mental health problems. However, these models focus on analyzing unique user's posts, not observing temporal behavior patterns, which are essential to track changes and evolution of emotional behavior and user context. The observation of mood indications involves the persistent analysis of feelings and characteristics over time. This article proposes the *TROAD* framework for longitudinal recognition of sequential patterns from depressive users on social media. *TROAD* collects and preprocesses the timeline of depressive users on Reddit. The framework identifies the best interval to analyze every user activities, extracts emotional and contextual features from user data, and models the features into time windows. Then, we extract sequential patterns from depressive user behavior. The main characteristics of context and emotions demonstrated by the users and found in the top-10 rules are negative emotions, such as: violence, pain, shame, depression, sadness, and silence. We obtained strong sequence patterns with a minimum of 70% of support, 81% of confidence, and 69% sequential confidence, considering silent windows, where users manifested no activity. Without considering silent windows, the rules showed respectively 70%, 86% and 38% of support, confidence, and sequential confidence.

TROAD computational approach is a promising tool to assist clinical specialists in future interventions.

- **keywords:** affective computing, depression, emotion recognition, sentiment analysis, sequence pattern mining, user behavior, temporal analysis, social media, online networks.

6.1 Introduction

Depression is one of the most prominent and growing disorders in the world. The World Health Organization - WHO (World Health Organization and others, 2017) estimates that 20% of the population will experience mood disorders at some point in life. Depression has been characterized as a mood disorder in which emotional and motivational conditions are the most compromised components. It comprehends many symptoms like a persistent feeling of sadness, a decrease of interest in engaging in activities that would be typically pleasurable, with impairment of routine and daily activities along two weeks at least. Also, there is an increase in anxiety, reduced concentration, feelings of guilt, hopelessness and worthlessness, suicidal ideation, among others (American Psychiatric Association and others, 2013; World Health Organization, 2020).

Traditionally, mental health professionals have primarily used clinical examination techniques based on self-reporting of emotional, behavioral, and cognitive dimensions to diagnose and monitor the condition's evolution. Examples of examination techniques are questionnaires, interviews, inventories, and other standardized instruments. Even though there are successful therapies for mental illnesses, between 76 and 85 percent of people in low and middle-income countries do not receive proper mental care (WANG *et al.*, 2007).

The lack of funding, qualified health providers, and the social stigma associated with mental illness are barriers to successful treatment. The imprecise evaluation is another obstacle to successful clinical care (World Health Organization, 2020). Although the processes and psychological instruments for detecting mood disorders have been improved and specialized to allow an earlier diagnosis, access to care is still limited.

In the last decades, the growing access to the internet and connected devices has encouraged users to interact and register their everyday feelings and opinions online. Among the most popular social networks are Reddit, Facebook, Twitter, and Instagram. Online social networks are potential tools for specialists in human behavior, such as psychologists, psychiatrists, and therapists, given the extensive sharing of personal user data online, contributing to provide patients' extra information to specialists (PAUL; DREDZE, 2014; GIUNTINI *et al.*, 2020; GAO *et al.*, 2020; YAZDAVAR *et al.*, 2020; Alghamdi *et al.*, 2020). For example, a specialist could take advantage of an existing platform's emotional reports (with previous consent). Then, the specialist can combine the discovered information with the patient's evaluation in a face-to-face service (limited by the hour) to improve the evaluation of the patient's mental state. In this context, changes in online users' behavior can provide meaningful mental illness indicators and trigger health care systems to produce automatic analysis and reports to inform specialists and allow early interventions, even before feelings worsen (ORGANIZATION *et al.*, 2017; ALGAN *et al.*, 2019).

Computational support is still considered insufficient to provide a precise diagnostic or complete support of human behavior specialists (HOLLIS *et al.*, 2015; SHEPHERD *et al.*, 2015). Works from the literature have focused on the extraction of emotional characteristics and identifying feelings from individual posts without considering aspects of temporal and longitudinal analysis, *i.e.*, the user's timeline and history (DYSON *et al.*, 2016; YAZDAVAR *et al.*, 2020; GIUNTINI *et al.*, 2020).

In contrast, organizations such as Word Health Organization (WHO) (World Health Organization and others, 2017; World Health Organization, 2020), and American Psychiatric Association (APA) (American Psychiatric Association and others, 2013), as well as the traditional evaluation protocol followed to identify mood disorders, all strongly recommend observing patients' feelings for a while. Many psychological disorders involve perseverative patterns of cognition, affect, and behavior. However, in depressive disorders, studies point to the propensity of persistent negative feelings in the individuals' lives, despite the circumstances and environment (KUPPENS; ALLEN; SHEEBER, 2010; PANAITE *et al.*, 2019). This specific pattern, named emotional inertia (SULS; GREEN; HILLIS, 1998), contributes to the severity of depressive symptoms in people diagnosed with depression (PANAITE *et al.*, 2019) and can be considered a risk factor for the development of the mental disorder (BROSE *et al.*, 2015). Therefore, if this characteristic tends to persist in the lives of depressed individuals, a pattern of negative responses may also be persistent in different environments in which these people communicate, such as on social networks.

Traditional methodologies provided by different associations point to the necessity for long-term evaluations. The methodologies focus on providing information that a post contains depressive emotions without matching aspects of the user's contexts, personality, or the user history on the network, that is, the user's timeline. The given information shows that a single user post can hardly predict mood disorders and other mental disorders, working only to inform the polarity of sentiment and emotion in a specific event. In contrast, analyzing user behavior changes over time can discover interesting information and indicators regarding different users.

Sequence pattern mining approaches can provide longitudinal analysis and predictions in different contexts and applications, *e.g.*, stroke prediction (Nasingkhun; Songram, 2018), crime location prediction (SUJATHA; EZHILMARAN, 2016), prediction of cerebellar ataxia based on body activity detected by sensors (Jin *et al.*, 2020), opinion analysis on Twitter (*e.g.*, during the American pre-election campaign) (Diaz-Garcia; Ruiz; Martin-Bautista, 2020), stress detection using smartphones (Alibasa; Calvo; Yacef, 2019). Temporal analysis of feelings in social networks has to be subject of a study aiming to extract characteristics of feelings, mainly in specific contexts, such as from students, regions, workers, and visual analysis over time, without considering specific approaches of sequence pattern mining (CHOUDHURY *et al.*, 2013b; CHOUDHURY; COUNTS; HORVITZ, 2013; SEABROOK *et al.*, 2018; CHEN *et al.*, 2018; YAO *et al.*, 2020; PRIMACK *et al.*, 2021).

In this work, we take into account the need for longitudinal approaches to assess the depressive behavior of users in social networks. Considering the potential use of mental illness indicators by domain experts to meet the functional requirements of the behavior analysis area, we investigate the following research questions:

- *Is it possible to describe emotional and behavioral patterns of depressed users on social networks through sequence pattern mining?*
- *What feelings, emotions, and contexts can occur together and which are predictors of others?*

To answer the research questions, we propose *TROAD*, a framework for the collection, preprocessing, modeling, and knowledge discovery of sequential patterns of user emotions from social networks.

Accordingly, the proposal of *TROAD* in this work contributes with:

- The collection of the timeline of depressive users in social media and the extraction of emotional features validated by specialists considering contextual aspects of users' posts.
- A flexible approach to model and discretize the users' timeline in the form of a time series, considering that (i) each user has a posting frequency and (ii) there is no common frequency pattern that describes all users.
- A methodology for discovering sequential patterns describing the behavior of depressive users on social networks. This methodology aims at supporting the observation of feelings and emotions occurring concomitantly and sequentially in a period of 15 days.

Paper outline: The remaining sections of this work are organized as follows. Section 6.2 presents related work. Section 6.3 describes the material and methods. Section 6.4 details the experimental results. Section 6.5 presents the discussion and takeouts from the literature. Finally, Section 6.6 gives the final remarks.

6.2 Related Work

This section presents previous studies focused on the temporal analysis of depressive users on social media. We use the following research string to search for the related studies:

((“temporal” or “longitudinal” or “sequential”) and (“depression” or “mood”) and (“social media” or “social network”)).

Table 6.2 summarizes the related studies, with the main features considered in this work, including how the study performed data collection, what are the main approaches employed, if the authors used social networks and information sources, and the media used for the analysis. Also, the table informs in which context the work was conducted and how is the temporal analysis performed in corresponding work.

In the studies (CHOUDHURY *et al.*, 2013b; CHOUDHURY; COUNTS; HORVITZ, 2013), the authors conducted a survey asking the Twitter users in the United States about their feelings with questions of the Center for Epidemiologic Studies Depression Scale (CES-D) (SHEEHAN *et al.*, 1995; EATON *et al.*, 2004), and collected the Twitter profile of the user. The authors analyzed the users’ activities for a year, counted the frequency of posts and replies, and created a Graph-based on user relations. To extract the expression of emotions and linguistic style, they use the LIWC lexicon[1]. The authors conducted a longitudinal analysis plotting the user features along the time, and the results showed a decreased social interaction, increased negative affect, strongly clustered ego networks, increased relational and medicinal issues, and increased religious involvement.

Seabrook *et al.* (2018) used a mobile app to collect and analyze the frequency of negative expressions in texts associated with depression of 49 Twitter users and 29 Facebook users located in Australia. The authors also evaluated the connection between depression intensity and the volatility and consistency of emotion. They extracted features using LIWC and performed a temporal analysis, comparing the differences among distinct social media platforms. The results show that the instability of negative expressions is a predictor of severe depression on Facebook and lower depression severity on Twitter.

In study (CHEN *et al.*, 2018), the authors analyzed sentiments, activities, and linguist styles of users on Twitter to detect depression. The author collected posts containing the expression “I was/have been diagnosed with depression” for four months, using the official API. They used the EMOTIVE ontology semantic model to recognize Ekman’s basic expressions of emotions: sadness, surprise, anger, fear, disgust, and happiness (EKMAN; SORENSON; FRIESEN, 1969; EKMAN; FRIESEN, 1971; EKMAN, 1993). As a result, the authors produced a descriptive temporal analysis plotting the features along the time.

Aalbers *et al.* (2019) conducted a survey with 125 Amsterdam students asking about their use of social media on smartphones. The goal was to measure passive use of social media, correlate it with depression symptoms using the multilevel auto-regressive time-series model, and model the data in a network form. The authors concluded that features related to the passive use of social media, *e.g.* the time scrolling the feed page, are not a good predictor of depression or

[1] The LIWC lexicon: <www.liwc.net>

stress symptoms. However, much time in passive mode can predict high levels of fatigue, interest loss, concentration problems, and fatigue and loneliness symptoms can predict the passive use of social media. In the same research direction, Heffer *et al.* (2019) conducted a survey and implemented an auto-regressive analysis to investigate the correlation between social media use by Canadian adolescents and depression symptoms in a long-term period. The study concluded that the use of social media does not predict depression in girls or boys, but severe depression predicts the use of more intensive social media by girls.

Yao *et al.* (2020) collected posts of a community of depressive users on the Sina Weibo (weibo.com) Chinese social network, using the official API. The authors applied K-means (Krishna; Narasimha Murty, 1999) and Pearson's chi-square (SHIH; FAY, 2017) over the data to investigate the frequent use of negative emotional terms and their correlation with depression. The results suggest that depression users are more active and express more negative terms, and depression is characterized by demonstrating three times more negative terms, on average, during the first month of social media use, in which the depressed symptoms are more evident in comparison to other periods.

Wang, Liu and Zhou (2020) analyzed a published database constructed with blogs and Twitter posts to identify and predict mental disorders in six different occupations (waiters, reporters, engineers, travelers, musicians, and comedians), with different levels of stress. The authors used the Sentiment140 lexicon (GO; BHAYANI; HUANG, 2009) to extract emotional features and the FP-Growth (AGARWAL; SRIKANT *et al.*, 1994) algorithm to discover frequent patterns. The results show that depression disorder contains the "sadness" emotion with 0.86 of intensity. Bipolar disorder is formed by "sadness" with 0.298 of intensity. However, the anxiety disorder contains mixed features occurring in the same sequence: "sadness" (0.088), "despair, pain, hope, concentration, sadness" (0.812), "anxiety, intimacy, trust, pain, confidence, tired" (0.89).

Among the works mentioned above, the studies (AALBERS *et al.*, 2019), and (HEFFER *et al.*, 2019) conducted a longitudinal analysis, but did not analyze the content of social media. Only the study (CHEN *et al.*, 2018) approached a broad context, while the others are applied to specific locations or audiences. Studies (CHEN *et al.*, 2018), and (YAO *et al.*, 2020) used specific APIs for the direct collection of social networks' data. The study (WANG; LIU; ZHOU, 2020) used a database published in previous work, while the others studies relied on questionnaires. Although the described studies conducted temporal analyzes over social media data, only study (WANG; LIU; ZHOU, 2020) used an approach based on sequence pattern mining, while the others just arranged collected information and features over time.

In general, the study described in this section analyzed the user data as a whole, not addressing and identifying the user behavior individually. In this work, we propose a framework to investigate sequence patterns discovered from users' posts, comments, and replies along time to fill this gap. Then, we model users' behavior in the form of time sequences. Each sequence is constituted by the emotional features extracted from the users' complete timeline on social media. We detail the proposed framework in the next section.

Author	Data Collection	Main Approaches	Social Network/Source	Media	Experiement Context	Temporal Analysis
Choudhury *et al.* (2013b), Choudhury, Counts and Horvitz (2013)	Survey	LIWC, ego-networks, frequency analysis	Twitter	Text	US	Visual
Seabrook *et al.* (2018)	Smartphone app	LIWC and frequency count	Facebook/Twitter	Text	Australia	Visual
Chen *et al.* (2018)	API	Emotive (Ontology Semantic Model)	Twitter	Text	General	Visual
Aalbers *et al.* (2019)	Survey	Activity counting, Graph	Not aplicable (Smartphone/Prompts)	Activity	Amsterdan students	Visual
Heffer *et al.* (2019)	Survey	Auto-regressive cross-lagged path	Not applicable (just survey)	Questions	Canadian Students	Visual
Yao *et al.* (2020)	API	K-means and Pearson's chi-square	Sina Weibo	Text	China	Visual
Wang, Liu and Zhou (2020)	Publish Database	Sentiment140 lexicon and FP-Growth	Blogs/Twitter corpus	Text	Professional workers	Sequence Pattern Mining
Primack *et al.* (2021)	Survey	9-Item Patient Health Questionnaire	Qualtrics Sampling Services	Questions	US	Visual
Proposal: *TROAD*	API	Empath and PrefixSpam	Reddit	Text and Emoticons	General	Sequence Pattern Mining

Table 12 – Summary of Related Works

6.3 Material and Methods

This section describes the methodology employed to collect, model, filter, and process the data acquired from users over time. We propose the *TROAD* framework (***Tr**acing the **Roa**dmap of **D**epressive Users*), which models the collected data into time windows, classifies emotions from users' posts, comments, and replies, and discovers sequential patterns from users' emotions.

6.3.1 Data Collection and Filtering

Figure 23 illustrates the pipeline for data acquisition and user filtering. We chose the Reddit social network because it has specific mutual support communities for diverse themes, including depression. Also, the official Reddit API makes the data collection task less bureaucratic and accessible than other platforms. We developed (i) a data crawler using the official Reddit API and downloaded posts, comments, and replies from the */r/depression* subreddit. In total, (ii) the crawler retrieved 415,459 user records, 778,822 posts, and 1,573,858 comments and replies from January 1st, 2009 until July 1st, 2019.

The average of posts and comments per user is 3.8, but this information is not evenly distributed since a large portion of the users has posted and commented only once in the period we collected the data. Thus, (iii-iv) we filtered the collected data in order to maintain only users that were active in the community for at least 15 days, resulting in 1,212 frequent users. The users were de-identified, generating random IDs to follow the Ethics protocol defined for this research.

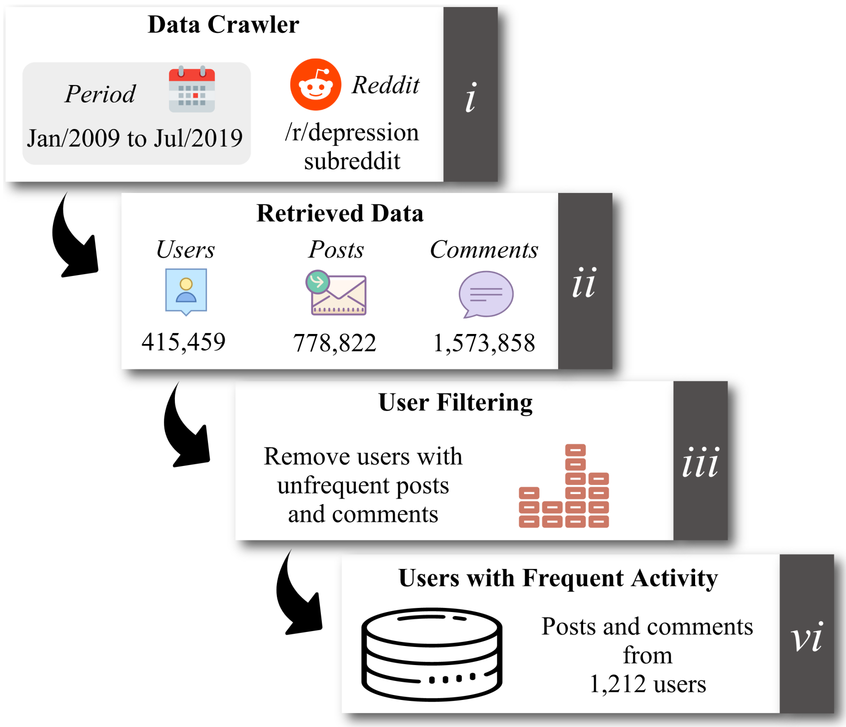


Figure 23 – Steps to collect, organize, and filter user data from Reddit.

Algorithm 2 – *TROAD*

Input: *dataset:* data from users acquired via API
intervalSize: number of days to analyze the user behavior
w: number of windows to split the user timeline
Output: *sPatterns:* sequential patterns discovered from all users

```
1: featuresFromAllUsers ← [] // Initialization
2: for each user in dataset do
3:     userData ← GetRawUserData(user, dataset)
4:     // Data cleaning and standardization
5:     userData ← PreprocessRawData(userData)
6:     // Data selection and transformation
7:     userTimeline ← ProcessTimeline(userData, intervalSize, w)
8:     // Extract emotional and contextual features
9:     userFeatures ← ExtractFeatures(userTimeline)
10:    featuresFromAllUsers.Add(userFeatures)
11: end for
12: // Extract patterns of user behavior
13: sPatterns ← getSequentialPatterns(featuresFromAllUsers)
14: Return(sPatterns)
```

6.3.2 The TROAD Framework

After collecting the data from Reddit, we employ *TROAD* to model the collected information and extract frequent patterns from the expressed emotions. Algorithm 2 details the main step of *TROAD*, which receives as input:

- *dataset*: raw user data collected using the Reddit API
- *intervalSize*: number of days in which the algorithm will look for frequent activity of every user
- *w*: number of windows that *TROAD* will split the time interval

As output, *TROAD* returns:

- *sPatterns*: sequential patterns discovered from users' timelines

The output include the temporal rules with the items of emotional and contextual features, the corresponding support and confidence values, and also a visual representation of the rules.

The algorithm starts (Line 1) initializing the set of features, which will receive features' time series extracted from user data. For each user in the input data set (Line 2), the algorithm extracts (Lines 3-10) the corresponding time series composed of emotion and context features. *TROAD* (Line 3) selects the data corresponding to the current user, and (Line 5) preprocesses the information to remove tags, stopwords, lemmatization, stemming, and special characters (maintaining the emoticons). Then, (Line 7) the algorithm processes the user data to select the best interval to analyze the user data based on a phase-shift heuristic. With (Line 9) the user timeline from the selected time interval, *TROAD* extracts emotional and contextual features corresponding to the user activity, (Line 10) adding them to the set of features *featuresFromAllUsers*. Finally, (Line 13-14) *TROAD* employs a sequential pattern mining algorithm to discover patterns from all users' timelines, returning the patterns as output. Following we detail every function of *TROAD*.

Data Cleaning and Transformation (*PreprocessRawData*): We preprocessed the raw user textual data with the NLP-preprocessing library NLTK (LOPER; BIRD, 2002), following the literature's classic steps:

1. Removal of *html* formatting tags from the text, *e.g.*, "*I'm suffering*" to "*I'm suffering*".
2. Removal of special characters from the text, *e.g.*, `!#$%&'()*+,-./:;<=>?@[]^_{}~`.
3. Transformation of all expressions to lowercase, *e.g.*: "*I Wanna Die*" to "*i wanna die*".
4. Removal of terms that are not meant for the analysis, *e.g.* "*is*", "*the*", "*a*", "*or*", "*what*", and "*but*" because they do not provide meaningful information.
5. Stemming and lemmatization textual normalization, in order to generate radicals and decide whether to remove the word suffix.

Emojis and emoticons in social media can contribute up to 57% with the sentiment analysis process (Giuntini *et al.*, 2019; CAZZOLATO *et al.*, 2019a). Accordingly, in Step 2, we kept a set of characters representing emojis and emoticons due to their potential to represent emotions and add context and feelings to user posts. To check if a notation is an emoji or emoticon, we took as reference the respective categories in the database provided by Rodrigues *et al.* (RODRIGUES *et al.*, 2018b).

Data Selection and Transformation (*ProcessTimeline*): This study assumes seasonal episodes in our emotional features since we restrict our analysis to a community focused on depressive users. The most significant difficulty when analyzing Reddit's data is the lack of uniformity in users' frequency of posts and comments. To work around this problem, we apply a cut filter to weigh the user activity frequency and select active users during a period. For every user, *TROAD* looks for the period with more activity in the social network, and the selected period is further divided into time windows. We call the windows with no user activity *silent periods* and classify each of them with "silence" in the feature extraction step, which we explain later in this section.

TROAD transforms the user data into timelines for pattern discovery with a three-step discretization process:

1. **Frequency**: First, we understand the impact of different time window sizes within the user data specifics. Very short windows preclude informative inferences from sequences since the collected data has few posts. Significantly increasing the number of windows

requires the method to classify most of them as "silence", which adds minor semantics to the pattern discovery ("silence" is not an emotion) and increases the complexity of generating rules with of large itemsets.

Additionally, with long windows, we lose the subtleties of changes in emotions that we are interested in because a user may have many posts per window, and thus we lose the information of transition between moods of our user.

The average time interval between two posts in our selected series is of two days and 8 hours. Accordingly, we modeled our approach to work with a time interval of 15 days, which is the minimum number necessary for diagnosing depression, and a window size of 3 days. We consider a sequential analysis of users through 5 windows to meet the specialists' requirements in the analysis of human behavior *i.e.*, psychologists, psychiatrists, and psychotherapists. Bearing in mind that traditional methodologies for inference of mood disorders usually constitute employing questionnaires and interviews on at least 15 days. Specifically considering depression, the manifestation of sadness and other negative symptoms is estimated for two consecutive weeks. This results in 15 days of constant user activity tracking. Accordingly, we set the input parameters of Algorithm 2 interval of days $intervalSize = 15$ and number of windows $w = 5$.

2. **Sliding Window**: *TROAD* models every user's timeline as a time series, considering the posts/comments and corresponding timestamps. Figure 24 (a) illustrates this step, in which *TROAD* slides a window/interval of 15 days over the entire user time series, computing the corresponding phase shift (explained next) for every subdivision (window) of the selected interval. This step retrieves the time series interval with the highest user activity over the entire collection period.

3. **Phase Shift**: In this step, we divide the timeline into five 3-day windows. The timeline division is made so that most user activities are centralized in the window intervals. As Figure 24 depicts, *TROAD* chooses the phase that best centralizes the timestamps in each window. For this, our proposal employs a cost function based on phase shift to determine the window location. Equation 6.1 defines the linear cost function employed. Let S_i be the time series with n timestamp points of a user i, such that $S_i = \{\rho_1, \rho_2, \rho_3, \ldots, \rho_n\}$. Parameter $\phi \in \mathbb{R}^+$ is the phase shift which has a value between zero and the number of days in the window (*i.e.*, $0 \leq \phi < 3$ in our modeling).

$$\min_{\phi} \sum_{i=1}^{n} (\rho_i + \phi) \bmod (3) \tag{6.1}$$

In this step of *TROAD*, only users with at least 15 days of frequent and consecutive activity were maintained. We maintained users with silent windows (*i.e.* without user activity) within the period, but not at the first and last windows, since in this case, the time series would

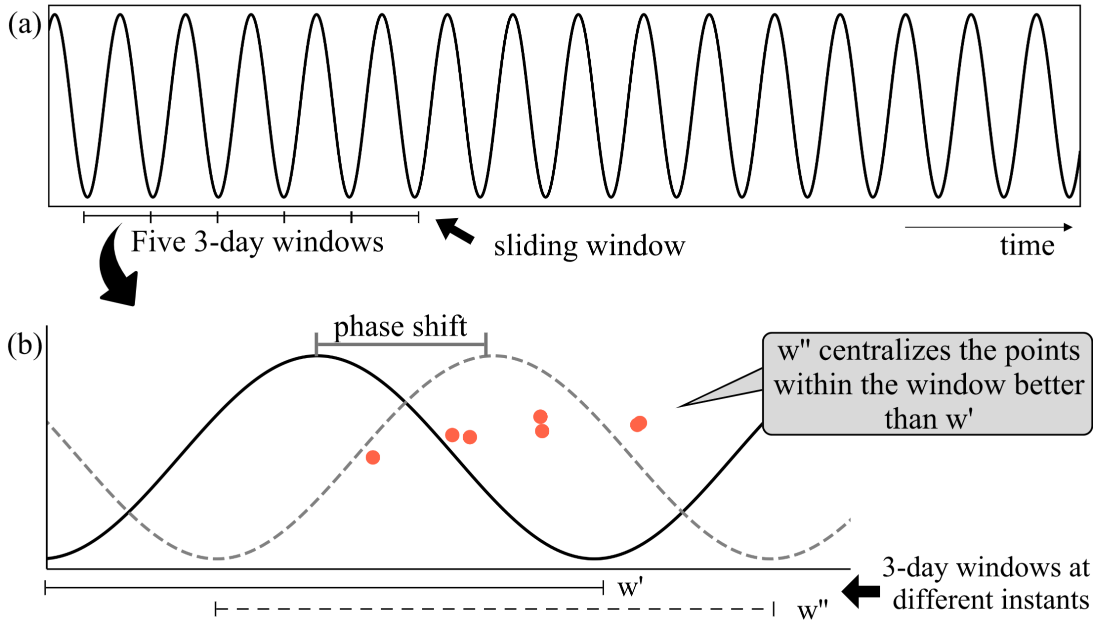


Figure 24 – Sliding window and phase shift to define the best interval of user data to process.

have size ≤ 15. After the filter pass over the collected data, we selected a total of 1,212 users with a time series considered adequate to perform feature extraction and analysis.

Emotional Feature Extraction (*ExtractFeatures*): All posts and comments were classified using the Empath lexicon (FAST; CHEN; BERNSTEIN, 2016). Six judges selected a subset of the words from Empath's dictionary to classify users' timelines, observing the classes reported on Empath library documentation. Three judges had experience in text mining and classification, and three judges are Psychology researchers. Initially, the project context was explained to specialists, considering the main depression characteristics reported by WHO (*e.g.*, persistent sentiments of pain, sadness, and a loss of interest in activities that enjoyed). Finally, we applied the Kappa coefficient (BANERJEE *et al.*, 1999; UNDERSTANDING. . . , 2013) and selected the features (classes) with 80% of agreement between the judges, listed in Table 13.

The selected features include positive (*e.g.*, "affection", "fun", and "enthusiastic") and negative (*e.g.*, "angry", "disgust", and "violence") emotion expressions, and contextual classes (*e.g.*, "politics", "exercise", and "work").

TROAD employs Empath with the selected classes to generate a feature vector from the user timeline corresponding to every window, separately. This results in a feature set $V = \{v_1, \ldots, v_w\}$, where w is the number of windows and $v_i | 1 \leq i \leq w$ is the feature vector extracted from the user timeline at window i.

Sequential Pattern Mining (*GetSequentialPatterns*): After obtaining the features from the timelines of all users, *TROAD* extracts patterns of user behavior. An association rule is $A \Rightarrow B$, which indicates that the set of items A implies in the set of items B. In this work, an item can

Empath classes selected in this study
affection, aggression, alcohol, anger, angry, annoyed, anticipation, cheerfulness, confusion, contentment, crime, death, deception, dejected, depressed, disappointment, disgust, dispute, dissatisfied, dominant, emotional, empathic, enthusiastic, envy, exasperation, exercise, expectant, fear, fight, friends, fun, giving, guilt, hate, healing, hesitant, horror, impatient, impressed, indignant, injury, irritability, joy, leisure, love, lust, miserable, negative_emotion, neglect, nervousness, optimism, pain, politeness, politics, poor, positive_emotion, pride, rage, ridicule, sadness, sexual, shame, suffering, surprise, timidity, torment, ugliness, violence, wedding, work

Table 13 – Words selected from the Empath dictionary.

be any of Empath's classifications (see Table 13). Support and confidence are two measures of interest employed to discover association rules (HAN; KAMBER; PEI, 2011). Let D be the dataset with all user features. The *support* of a rule is the probability of A and B occurring together in D, and is given by Equation 6.2.

$$\text{Support}(A \Rightarrow B) = \frac{|A \cup B|}{|D|} \tag{6.2}$$

The *confidence* of a rule assesses the degree of certainty of the rule, and is given by Equation 6.3.

$$\text{Confidence}(A \Rightarrow B) = \frac{|A \cup B|}{|A|} \tag{6.3}$$

Among the users presenting the feelings from set A, the confidence represents the probability of also having the feelings from set B, not necessarily in the next immediate window. However, we are interested in analyzing the user behavior within the time interval and in sequence. We employ the PrefixSpan (HAN *et al.*, 2001) sequential pattern mining algorithm to discover association patterns between sets of items that occur concomitantly and sequentially. The measure of interest employed is the *sequential confidence*, which informs how likely a set of items A from window w_i occur before a set of items B in the next immediate window w_{i+1} (*i.e.* $A_{w_i} \Rightarrow B_{w_{i+1}}$).

TROAD found strong sequential rules that describe the depressive behavior along time on social media. With the guidance of specialists, we defined a minimum support threshold of 70%, which resulted in a total of 356,258 sequential patterns. We present and discuss *TROAD*'s discovered rules in the next section.

6.4 Results

In this section, we present the sequential patterns discovered with the application of *TROAD* over the user data collected from Reddit. We consider a window size of 3 days for all experiments. However, we vary the number of windows from 1 – to check the occurrence of individual emotion expressions to 5 – which corresponds to an interval of 15 days, suggested by specialists as the optimal time interval to infer consistent user behavior patterns. In Subsection 6.4.1 we analyze patterns discovered considering only emotions detected from users. Subsection 6.4.2 analyzes the patterns considering emotions and silent periods, in which the user has no activity between two or more windows in the analyzed interval. In Subsection 6.4.3 we present the emotion transitions visually over time. Finally, in Subsection6.4.4 we present a discussion regarding sequential patterns containing contextual information extracted from the users' posts.

6.4.1 Sequential Patterns over User Emotions

First, we analyze the sequential patterns of user behavior without silent windows. Table 14 presents the top-10 discovered rules per the number of windows (from 1 to 5) and the corresponding support, confidence, and sequential confidence of the patterns.

Sequential Pattern (*Without Silent Periods*)	**Support**	**Confidence**	**Sequential Confidence**
Number of windows: $w = 1$			
negative	0.98	1.00	1.00
violence	0.97	1.00	1.00
pain	0.97	1.00	1.00
pain, violence	0.96	1.00	1.00
shame	0.96	1.00	1.00
negative, violence	0.96	1.00	1.00
depressed	0.95	1.00	1.00
positive	0.95	1.00	1.00
sadness	0.95	1.00	1.00
pain, shame	0.95	1.00	1.00
Number of windows: $w = 2$			
negative $\rightarrow$ negative	0.95	0.97	0.80
pain $\rightarrow$ negative	0.94	0.97	0.79
negative $\rightarrow$ pain	0.93	0.95	0.78
violence $\rightarrow$ negative	0.94	0.96	0.77
negative $\rightarrow$ violence	0.93	0.94	0.76
shame $\rightarrow$ negative	0.92	0.96	0.76

Table 14 continued from previous page

Sequential Pattern (*Without Silent Periods*)	Support	Confidence	Sequential Confidence
positive → negative	0.92	0.97	0.76
pain, violence → negative	0.93	0.96	0.76
pain, shame → negative	0.91	0.96	0.75
negative, pain → negative	0.92	0.97	0.74
Number of windows: $w = 3$			
negative → negative → negative	0.91	0.94	0.63
pain → negative → negative	0.89	0.94	0.63
negative → negative → pain	0.89	0.92	0.62
violence → negative → negative	0.89	0.94	0.61
negative → pain → negative	0.88	0.91	0.61
pain → negative → pain	0.87	0.91	0.61
negative → negative → violence	0.88	0.91	0.61
shame → negative → negative	0.88	0.93	0.60
positive → negative → negative	0.87	0.94	0.60
pain, violence → negative → negative	0.88	0.93	0.60
Number of windows: $w = 4$			
negative → negative → negative → negative	0.82	0.91	0.50
pain → negative → negative → negative	0.80	0.91	0.50
negative → negative → negative → pain	0.80	0.89	0.49
violence → negative → negative → negative	0.79	0.91	0.49
negative → pain → negative → negative	0.80	0.89	0.49
negative → negative → pain → negative	0.80	0.89	0.49
pain → negative → negative → pain	0.79	0.89	0.49
pain → negative → pain → negative	0.79	0.88	0.49
negative → negative → negative → violence	0.80	0.89	0.48
shame → negative → negative → negative	0.78	0.91	0.48
Number of windows: $w = 5$			

Table 14 continued from previous page

Sequential Pattern (*Without Silent Periods*)	**Support**	**Confidence**	**Sequential Confidence**
negative → negative → negative → negative → negative	0.71	0.88	0.40
negative → negative → negative → negative → violence	0.70	0.86	0.38

Table 14 – Discovered rules without silent periods: Top-10 sequential patterns discovered for different sequences of windows ordered by the sequential confidence.

For rules of $w = 1$, the only positive emotion expression was "positive", and most of the emotions occurred alone. The majority of rules generated with $w = 2$, $w = 3$ and $w = 4$ contain the emotional expression "negative". Notice that *TROAD* only found two frequent patterns for windows of size 5 (with a sequential confidence of up to 0.4), mainly composed of the "negative" emotion. Although the number of rules is smaller than the smaller number of windows, the two generated rules are significant for the user behavior analysis since they correspond to patterns observed 15 days, characterizing a recurrent pattern. At $w = 5$, it is possible to observe high confidence above 86%, but the sequential confidence is already lower at 38%. This is evident, as people can manifest patterns of individual and different emotional expressions, which may not be a pattern that describes the temporal order of the entire population analyzed. However, it can be an expressive pattern for 70% of users without a temporal order. Besides, the use of negative terms successively for four windows of time can predict a context of violence with high non-sequential confidence. We observe that "pain", "shame", and expressions of violence are always present in rules with negative emotions.

Regarding the emotions that occur in the same time window, "pain" and "violence" and "pain" and "shame" occur in the same period with $w = 2$. As the number of windows increases and, consequently, the analysis, negative emotions become more evident in the rules. The use of emotions that appear together ceases to appear for stricter rules. Rules with less trust can be consulted because even if they do not describe a typical pattern, they can describe the users' individuality.

Next, we analyze the generated patterns considering silent periods.

6.4.2 Sequential Patterns over User Emotions and Silent Periods

When posting on social networks, many users may present an intermittent activity. In this experiment, we address this behavior by including silent periods with the interval of postings analyzed from each user.

Table 15 shows the top-10 discovered sequential rules per the number of windows (from 1 to 5) and the corresponding support, confidence, and sequential confidence of the patterns. Again, the majority of items appearing in the frequent patterns relate to negative emotions. Interestingly, the item "silence" does not appear as one of the most frequent items for $w = 1$ and $w = 2$. However, for windows, $w \geq 3$, the silence period appears in all rules, which indicates that users frequently post content related to negative emotions interleaving periods of silence, *i.e.*, absence of social interaction in the community.

Sequential Pattern (*With Silent Periods*)	**Support**	**Confidence**	**Sequential Confidence**
Number of windows: $w = 1$			
negative	0.98	1.00	1.00
violence	0.97	1.00	1.00
pain	0.97	1.00	1.00
pain, violence	0.96	1.00	1.00
shame	0.96	1.00	1.00
negative, violence	0.96	1.00	1.00
depressed	0.95	1.00	1.00
positive	0.95	1.00	1.00
sadness	0.95	1.00	1.00
pain, shame	0.95	1.00	1.00
Number of windows: $w = 2$			
negative $\rightarrow$ negative	0.95	0.97	0.86
pain $\rightarrow$ negative	0.94	0.97	0.84
negative $\rightarrow$ pain	0.93	0.95	0.83
violence $\rightarrow$ negative	0.94	0.96	0.83
negative $\rightarrow$ violence	0.93	0.94	0.83
shame $\rightarrow$ negative	0.92	0.96	0.83
positive $\rightarrow$ negative	0.92	0.97	0.82
pain, violence $\rightarrow$ negative	0.93	0.96	0.82
pain, shame $\rightarrow$ negative	0.91	0.96	0.82
negative, pain $\rightarrow$ negative	0.92	0.97	0.82

Table 15 continued from previous page

Sequential Pattern (*With silent Periods*)	**Support**	**Confidence**	**Sequential Confidence**
Number of windows: $w = 3$			
negative → silence → negative	0.89	0.91	0.80
pain → silence → negative	0.87	0.90	0.79
shame → silence → negative	0.86	0.90	0.78
violence → silence → negative	0.87	0.91	0.77
negative → silence → pain	0.87	0.89	0.76
pain, violence → silence → negative	0.86	0.90	0.76
pain, shame → silence → negative	0.84	0.90	0.76
negative, pain → silence → negative	0.85	0.90	0.76
shame, violence → silence → negative	0.84	0.90	0.75
negative → silence → violence	0.86	0.89	0.74
Number of windows: $w = 4$			
negative → silence → silence → negative	0.83	0.88	0.77
pain → silence → silence → negative	0.81	0.87	0.75
shame → silence → silence → negative	0.79	0.87	0.74
violence → silence → silence → negative	0.81	0.87	0.74
negative → silence → silence → pain	0.81	0.86	0.74
pain, violence → silence → silence → negative	0.79	0.86	0.74
pain, shame → silence → silence → negative	0.78	0.86	0.73
negative, pain → silence → silence → negative	0.78	0.87	0.73
shame, violence → silence → silence → negative	0.78	0.87	0.73
negative → silence → silence → violence	0.81	0.86	0.73
Number of windows: $w = 5$			
negative → silence → negative → silence → negative	0.74	0.84	0.74
pain → silence → negative → silence → negative	0.72	0.83	0.72
shame → silence → negative → silence → negative	0.71	0.83	0.72
violence → silence → negative → silence → negative	0.71	0.83	0.72

Table 15 continued from previous page

Sequential Pattern (*With silent Periods*)	**Support**	**Confidence**	**Sequential Confidence**
negative → silence → negative → silence → pain	0.73	0.82	0.71
pain, violence → silence → negative → silence → negative	0.70	0.82	0.71
negative → silence → negative → silence → violence	0.72	0.82	0.70
negative → silence → pain → silence → negative	0.72	0.81	0.70
pain → silence → negative → silence → pain	0.71	0.81	0.70
shame → silence → negative → silence → pain	0.70	0.81	0.69

Table 15 – Top-10 sequential patterns discovered for different sequences of windows ordered by the sequential confidence.

Considering only one window ($w = 1$), emotions “pain”, “violence”, “negative” and “shame” appeared together and combined. In the span of two-time windows ($w = 2$), the emotion “violence” appeared in most discovered rules, also co-occurring with “pain” within the same window. Considering $w = 3$ and $w = 4$, most of the discovered patterns show silence periods with the detected emotions. Finally, considering a period of 15 days ($w = 5$), most of the discovered rules show that users expressed themselves with posts, comments and replies with the emotions “negative”, “pain”, “shame”. Again, the rules present periods of silence with no user activity.

The sequential rules of several extensions, that is with $w > 2$, demonstrate in all periods that the depressed user has participation in intermittent posting, that is, that fluctuates over time. It breaks the common myth that the depressed user does not post on the network or is just a passive user who scrolls the page. Although the user was silent, that is, they did not post or did not comment in the period, they may have participated in other ways, such as reacting to the content whether they like it or not (upvote or downvote on Reddit). Consequently, tracking periods of silence allowed us to extract solid sequential rules over a more extended period, contributing significantly to the sequence pattern mining. This fact is more evident with $w = 5$, because without periods of silence (Table 14), the algorithm extracted just two rules with a minimum confidence of 0.86 and temporal confidence of 0.38. Considering periods of silence, as shown in Table 15, it is possible to extract the top-10 rules with a minimum confidence of 0.81 and minimum sequential confidence of 0.69. The rules showed varied characteristics such as “pain”, “shame”, “violence”, and items co-occurring in the same window, such as “pain” and “violence” implicating in “negative” emotions and periods of silence.

6.4.3 Visual Evaluation of Emotion Transitions

Figure 25 depicts the connections of all sequential patterns discovered regarding the detected sentiments expressed by users in posts, comments, and replies. We visually represent the patterns using a Sankey Diagram, where each node (vertical bars) corresponds to an item (*i.e.*, a sentiment), the links represent the co-occurrence of items in the same pattern, and every color represent a window of three days. The links between items of the same color (*i.e.*, belonging to the same window) correspond to items that occurred together in the window period. Notice that, although the windows are not evenly spaced to improve the visualization of the link transitions (*e.g.* $w = 1$ has more links and takes more space from the figure), all windows have the same size in the pattern discovery modeling (3 days). Links between items depicted in different colors correspond to an emotional transition, from one window to the immediately next to one.

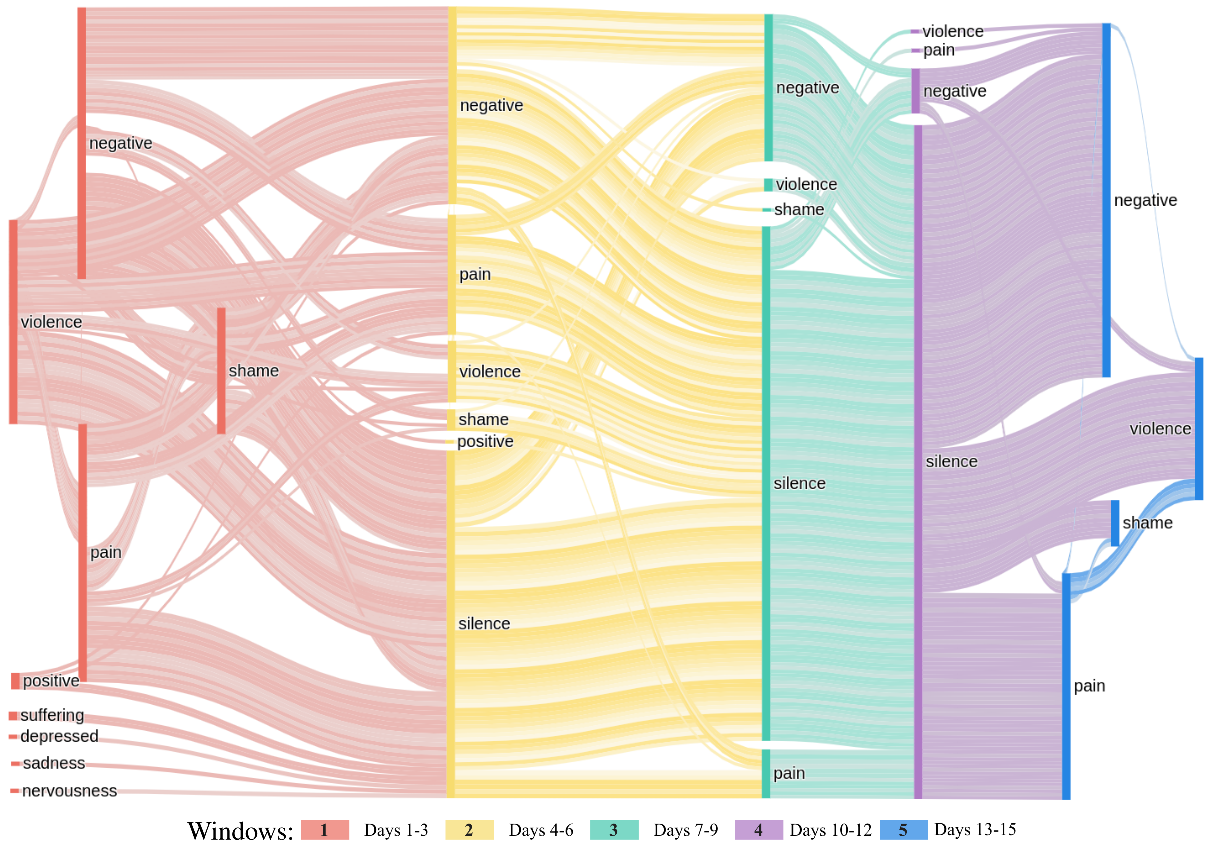


Figure 25 – Sequential patterns discovered from users' timelines during 15 days.

The majority of items relate to negative emotions. Within the first window, different pairs of items that occurred together, such as "violence",and "negative", "pain" and "shame", "violence" and "shame", and "violence" and "negative". Windows 2, 3, and 4 presented item transitions only between different windows. Notably, the "silence" item corresponds to a period (in this case, a 3-day window) in which the user has no activity in the social network. The "silence" item has the highest number of connections considering windows 2, 3, and 4. This pattern indicates that most users tend to spend periods of silence before and after posting content related to negative emotions, such as "violence", "pain", "shame", "negative". Finally, pairs of items occurring together also appeared within window 5, such as "negative" and "violence", "pain" and "violence", and "pain" and "shame".

6.4.4 Evaluation of Contextual Concepts Over Time

The top discovered rules relate to mostly negative feelings. However, one of the main features related to human behavior is contextual information. In this experiment, we focus on contextual features and select the top rules containing at least one of the contextual emotion expressions considered in our study:

- Contextual classifications: alcohol, crime, death, dispute, exercise, fight, friends, fun, healing, lust, neglect, pain, politeness, poor, sexual, violence, wedding, work

Since most of the top discovered rules presented in the sequential patterns analysis have "violence" as a frequent item (see Tables 15 and 14), we omit this class in this analysis when appears alone in the windows, to broaden the discussion regarding other contextual features.

The contextual items appear 385,019 times in the discovered patterns, and 260,106 patterns. Table 16 presents the top-10 discovered rules with contextual features. The top-10 rules showed features together in the same window, for $w > 2$, such as "pain" with "violence" and "pain" with "shame". The rules contained a minimum confidence of 0.80 and temporal confidence of 0.68. The rules call attention to how much the depressive pain and shame are evident in the patterns because even if the plot is different, these characteristics are strongly connected.

Sequential Pattern (*With Silent Periods and at Least One Contextual Item per Rule*)	**Support**	**Confidence**	**Sequential Confidence**
Number of windows: $w = 1$			
`pain`	0.97	1.00	1.00
`pain, violence`	0.96	1.00	1.00
`pain, shame`	0.95	1.00	1.00
`negative, pain`	0.95	1.00	1.00
`pain, shame, violence`	0.95	1.00	1.00
`negative, pain, violence`	0.94	1.00	1.00
`negative, pain, shame`	0.93	1.00	1.00
`pain, suffering`	0.92	1.00	1.00
`nervousness, pain`	0.92	1.00	1.00
`negative, pain, shame, violence`	0.92	1.00	1.00

Table 16 continued from previous page

Sequential Pattern (*With Silent Periods and at Least One Contextual Item per Rule*)	**Support**	**Confidence**	**Sequential Confidence**
Number of windows: $w = 2$			
`pain` → `negative`	0.94	0.97	0.79
`negative` → `pain`	0.93	0.95	0.78
`pain`, `violence` → `negative`	0.93	0.96	0.76
`pain`, `shame` → `negative`	0.91	0.96	0.75
`negative`, `pain` → `negative`	0.92	0.97	0.74
`pain` → `pain`	0.92	0.95	0.74
`negative` → `pain`, `violence`	0.91	0.93	0.74
`shame` → `pain`	0.91	0.95	0.74
`pain`, `shame`, `violence` → `negative`	0.91	0.96	0.73
`pain` → `violence`	0.91	0.94	0.73
Number of windows: $w = 3$			
`pain` → `silence` → `negative`	0.87	0.90	0.84
`negative` → `silence` → `pain`	0.87	0.89	0.83
`pain`, `violence` → `silence` → `negative`	0.86	0.90	0.83
`pain`, `shame` → `silence` → `negative`	0.84	0.90	0.82
`negative`, `pain` → `silence` → `negative`	0.85	0.90	0.82
`pain`, `shame`, `violence` → `silence` → `negative`	0.84	0.90	0.82
`pain` → `silence` → `pain`	0.85	0.88	0.81
`negative`, `pain`, `violence` → `silence` → `negative`	0.83	0.90	0.81
`shame` → `silence` → `pain`	0.84	0.88	0.80
`violence` → `silence` → `pain`	0.85	0.88	0.80
Number of windows: $w = 4$			
`pain` → `silence` → `silence` → `negative`	0.81	0.87	0.75
`negative` → `silence` → `silence` → `pain`	0.81	0.86	0.74
`pain`, `violence` → `silence` → `silence` → `negative`	0.79	0.86	0.74

Table 16 continued from previous page

Sequential Pattern (*With Silent Periods and at Least One Contextual Item per Rule*)	**Support**	**Confidence**	**Sequential Confidence**
pain, shame → silence → silence → negative	0.78	0.86	0.73
negative, pain → silence → silence → negative	0.78	0.87	0.73
pain, shame, violence → silence → silence → negative	0.78	0.86	0.73
pain → silence → silence → pain	0.79	0.85	0.72
negative, pain, violence → silence → silence → negative	0.77	0.86	0.72
shame → silence → silence → pain	0.78	0.85	0.72
violence → silence → silence → pain	0.79	0.85	0.71
Number of windows: $w = 5$			
pain → silence → negative → silence → negative	0.72	0.83	0.72
negative → silence → negative → silence → pain	0.73	0.82	0.71
pain, violence → silence → negative → silence → negative	0.70	0.82	0.71
negative → silence → pain → silence → negative	0.72	0.81	0.70
pain → silence → negative → silence → pain	0.71	0.81	0.70
shame → silence → negative → silence → pain	0.70	0.81	0.69
violence → silence → negative → silence → pain	0.70	0.81	0.69
negative → silence → negative → silence → pain, violence	0.70	0.80	0.69
pain → silence → negative → silence → violence	0.71	0.81	0.69
pain → silence → pain → silence → negative	0.71	0.80	0.68

Table 16 continued from previous page

Sequential Pattern (*With Silent Periods and at Least One Contextual Item per Rule*)	**Support**	**Confidence**	**Sequential Confidence**

Table 16 – Top-10 sequential patterns with contextual features discovered for different sequences of windows ordered by the sequential confidence.

6.5 Discussion and Takeouts from Literature

Even though the literature shows that depressive users express more negative emotions than other types of social network users (CHOUDHURY; COUNTS; HORVITZ, 2013; CHOUDHURY *et al.*, 2013b), the longitudinal pattern of responses of people with depressive disorders in these networks is still unclear (YAO *et al.*, 2020). Longitudinal evaluations could contribute to a more satisfactory diagnostic identification, as they allow monitoring the individuals' behaviors that are rarely identified in a clinical evaluation of a few minutes (RÍSSOLA; LOSADA; CRESTANI, 2019). Studies indicate that the responses of depressive users may present different patterns (WINOKUR, 1997; YAO *et al.*, 2020), and the identification of the characteristics of users, which justify these differences, still needs scientific investigation (RÍSSOLA; LOSADA; CRESTANI, 2019).

This study showed an increasing number of posts related to negative emotions over the observed interval (15 days), while positive emotions were expressed in isolation and only in this investigation's initial period. Difficulty in managing negative emotions is, in fact, common among people with depression. In general, they think repeatedly and uncontrollably about their depressive symptoms, their failure, and their negative experiences (NOLEN-HOEKSEMA, 1991), and they will be able to find spaces in virtual environments to express this experience, where they feel more familiar and safe (NESI; PRINSTEIN, 2015). In addition to this excessive focus on symptoms being able to trigger a spiral of negative thoughts and emotions (NOLEN-HOEKSEMA, 1991), sharing them on the network can attenuate the individual's view of problems and strengthen victimization by other users, in an attempt to provide emotion-focused support. Some authors explain that posts related to negative emotions can increase the chances that other users will also post messages related to these emotions (KRAMER; GUILLORY; HANCOCK, 2014), which contributes to the co-rumination, perpetuation, and intensification of symptoms of depression among users (EHRENREICH; UNDERWOOD, 2016).

Posts of content related to negative emotions by users are interspersed with periods of silence (absence of interaction on the social network), leading to the understanding that there are possible fluctuations in mood. Considering that an active participation in the social network, with a more significant number of posts related to negative emotions, may show a period of intensification of depressive symptoms (NESI; PRINSTEIN, 2015), the absence of activities could evidence a period of symptom stability. Some research indicates that mood instability is positively correlated with depression, contributing to the duration of the overall experience of depression and stressful events (BOWEN *et al.*, 2013; PATEL *et al.*, 2015). Such instability can be part of a disordered depressed mood, as well as it can be parts of other disorders, such as anxiety disorders, borderline personality disorders, or substance abuse (BOWEN; CLARK; BAETZ, 2004; EBNER-PRIEMER *et al.*, 2007; PATEL *et al.*, 2015). Therefore, the longitudinal assessment of users on the network is a way of measuring the overall experience of depressed mood, which is generally not identified during a regular clinical assessment.

The contents that preceded the silence periods identified in this study were related to pain, violence, and shame. Once latent symptoms end up being expressed and identified on social networks, they are likely to be related to traumatic and stigmatizing experiences (HOMAN *et al.*, 2014). Depression is frequently observed among people who experience chronic painful experiences (KROENKE *et al.*, 2011) and people who are victims of violence (FAZEL *et al.*, 2015). Nevertheless, just as many people express their problems related to depression on social networks, they post content related to the difficulty to live with the experience of pain (SENDRA; FARRé, 2020), and which are characterized by relationships of abuse and violence (SCHRADING *et al.*, 2015).

Among the users participating in this study, the word "violence" was related to the words "negative" and "pain". In (WUEST *et al.*, 2010) the authors point out that experiences of pain and violence may be related and also corroborate the theory that stressful events, such as child abuse and domestic violence, may contribute to the etiology or maintenance of chronic pain (DAVIS; LUECKEN; ZAUTRA, 2005; WUEST *et al.*, 2010). The word "shame" was also prevalent in the posts and was related to the word "pain". Shame is related to depression, and because it includes forms of embarrassment and humiliation, it can be related to social pain (ELISON; GAROFALO; VELOTTI, 2014). The shame is identified in the literature as the leading cause of rumination, especially when events focus on damage to self-esteem, lack of control, or social inadequacy.

The framework proposed in this study was able to describe a set of sequential patterns of behavior discovered from depressive users' activities in the social network Reddit, which were also reported and supported by literature of mental health as evident characteristics in people with depression clinic. This denotes the potential of *TROAD* to be used as an auxiliary method for assessing mood disorders manifested in virtual environments, such as social networks.

6.6 Conclusions

In this work, we proposed *TROAD*, a framework to evaluate the behavior of depressive users on social media. The framework collects user activity (posts, comments, replies, and emojis) from the Reddit depressive community */r/depression* subreddit, preprocesses and models the data into five consecutive windows of three days each. Accordingly, we analyzed the social activity as timelines of 1,212 users during 15 consecutive days, a period considered adequate by specialists to evaluate possible mental disorders, such as depression (World Health Organization, 2020).

TROAD discovered sets of sequential patterns from user emotions and contextual features. The most significant expressions in the top-10 discovered rules are "negative" emotion, "violence", "pain", "shame", "depression", and "sadness". We also modeled the rule extraction step of *TROAD* considering silent periods, in which the user presented no activity (*e.g.*, post or comment) in the social network during the observed interval. In this scenario, "silence" appears in most of the discovered rules. The obtained top-10 patterns presented strong rules that describe the emotional and contextual aspects of depressive behavior, considering both the presence or absence of user activity in specific periods. In summary, we highlight the following contributions of *TROAD*:

1. The framework can evaluate the emotional behavior of depressed users and provide emotional and contextual information from users' activities in a depressive community.

2. The flexible approach for user data discretization over time windows allows analyzing users' timelines as time series, considering the irregular non-normalized frequency of posts.

3. The framework provides a methodology for pattern discovery of sequential rules that describe the behavior of depressive users on social networks over time.

As future work, we intend to:

- Employ the discovered rules to infer information from users on a Web or mobile platform. In this case, with the users' consent, the application would synchronize the users' activity and allow their therapists to observe behavior changes over time. With user monitoring from public social media, the application will extract metrics that potentially assist specialists in assessing the effectiveness of the current therapy or even assist in changing the treatment approach. Likewise, it is possible to implement a general and public solution. If the system automatically perceives any depressive pattern, it triggers warnings so that mental health specialists can get in touch with the user and conduct an intervention.

- Explore the proposed framework in analyzing of other mental health disorders, such as anxiety, schizophrenia, bipolarity, among others.

- Adapt *TROAD* to work in new environments and technologies to find depressive behavior patterns, such as in smart homes for indoor monitoring and mobile devices, to track outdoor behaviors.

Ethics Committee Approval

This research has the Ethics Committee's approval from the School of Arts, Sciences and Humanities (EACH) of the University of São Paulo, Brazil, under register number 88799118.8.0000.5390.

CHAPTER

7

CONCLUSIONS

In this Ph.D. research, an approach to the sequential evaluation of emotional behaviors of depressive users on social networks, which analyzes (i) the behavioral pattern of depressive users in a group, their feelings, and how they interact and group themselves in communities. And (ii) frequent temporal patterns of individual user behavior in the form of sequential rules. In both approaches, information from the posts and comments of users of the Reddit social network was used, and the content could include texts and emoticons.

Additionally to the approaches (i) and (ii), the use of emoticons for sentiment analysis was validated by a methodological process that involved surveying social media users, judges validation strategy with human behavior specialists, and employing a clustering algorithm based on Expectation and Maximization. In this study, the manifestation of emotions shown on the social network (virtual environment) was correlated with emoticons with the Ekman's (EKMAN; SORENSON; FRIESEN, 1969) universal emotions demonstrated in real life.

This Thesis was oriented to answer the challenges presented in the systematic review of the literature presented in chapter 2. The review demonstrated which there are a lot of advanced algorithms for extract emotional and contextual features. The study showed that the primary studies in recognizing depression on social networks context focused on determining the presence of depression based on a single post and did not evaluate the manifestation of emotions or feelings sequentially. In contrast, the mental health literature argues that the analysis of depression requires observing the manifestation of symptoms in the long term, needed to consider aspects of personality and context, demonstrating that depression can involve different characteristics. Therefore, pointing out depression in a single post, yes or no, could not be representative, considering a semantic difference in being sad at a specific isolated moment with being depressed. Some peculiarities the algorithms are not able to detect mainly lead to subjectivity. Simultaneously, there is a demand for specialists to use the extra information of their patients, and that provided in consultation through interviews or questionnaires. Thus, it is noted that it would be interesting for a computational solution to identify the manifestation of characteristics in the long term and to find sequential emotional patterns that could predict feelings. With this, the main Ph.D research is answered the research questions presented on section 1.1: *"How recognizing temporal patterns of depressive users on social network?"*. This question is challenging since user behavior on social networks is dynamic, complex, and very personal. Dynamic, because the network updates quickly, people change relationships and topics of interest, and have dynamic posting frequency; complex because the data is unstructured and complex, and the language is colloquial, personal, because context is global, each user has a personality and behaves differently, showing different characteristics.

From this scenario, we obtained the following contributions:

1. Discussions of the state of the art provide by a systematic review of previous works on recognition of depression on social media, including challenges and open issues.

2. A clustering mechanism to recognizing expression of emotions on social media by emoticons (Facebook reactions), including a published a open dataset of the study;

3. An methodology to modeling and assessing the temporal behavior of emotional and depressive user interactions on social media (Group analysis);

4. The TROAD framework for recognizing the sequential behavioral patterns of depressive users on social networks based on emotional and contextual features presents on user's timeline (Individual Analysis).

5. Extraction of the depressive user-behavior patterns in groups and individually.

In regarding the limitations described in systematic review (3.5, this work consider that supply the challenges 1 (focus only on the analysis of textual information from postings, log activities, or demographic characteristics of the users' profile), 2 (did not properly explore the associated media), 3 (did not consider the users' context and temporal analysis), and 4 (did not evaluate the interactions).

In regarding the thesis of the Ph.D research:

It is possible to describe strong behavioral patterns of depressive users on social media by extracting (i) emotional characteristics of posts and comments, (ii) mining sequential and individual patterns, and (iii) evaluating their interactions modeling by complex networks over time.

This thesis is formed by a set of articles, in which each one seeks to supply a specific gap and answer a subquestion that together makes up this thesis. The discovery of the research gaps was found through a systematic review that makes the literature review process and discussion of related works reproducible, allowing to find gaps that are definitely important for these contexts. Based on the gaps and the extracted knowledge, this work proposes an approach, which comprises the (i) approach that analyzes the interaction behavior of depressive users in groups using complex networks, described in the chapter 5, and the (ii) an approach that analyzes individual sequential patterns, described in the chapter 6. In both approaches (i) and (ii), it is considered texts and emoticons of posts and comments in the process of analysis of feelings, whose use of emoticons is based on the chapter 4. In all studies, a validation of the computational results found was compared and validated by the literature in the area of mental health and analysis of human behavior. With that, the answer to this thesis is "Yes," it is possible to strongly describe behaviors of depressive users through the extraction of characteristics and by the mining of individual sequential patterns, using sequence pattern mining, and evaluating the interaction behaviors through networks complex.

A point to note is that the objective was to recognize the temporal patterns of depressive users on social networks. Although we found evidence in the literature about the representativeness of these patterns in real life, the work was not aimed at and not able to address all the dynamics of life and context, which are complex. However, the extracted indications have a strong potential to assist in traditional assessments of behavior analysts.

7.1 Limitations and Threats to validity

Among the limitations of this work, it is worth mentioning some points of attention:

- The results described in each chapter reflect the behavior patterns manifested by users only in social networks, according to the research questions described in chapter 1 and sub-question of each chapter. Although the results showed a high confidence rate through computational metrics, they may not necessarily be fully manifest in the real environment. Monitoring the differences between real and virtual, in addition to escaping a little from research and experimental control, can involve issues such as the user self-projecting with a different personality and mood.

  However, it is worth mentioning that for specific research investigations, these points can be fundamental. For example, a) a study of depression in students, children, and adolescents or b) differences in depression in western and eastern countries.

- This work proposed to identify emotional behaviors through posts on social networks in general, that is, without differentiating aspects such as age, gender, culture, religion, language, and writing pattern, considering that social networks are used globally and English it is the global and scientific writing standard.

- The results described were not compared with different groups, as we used an explanatory and descriptive approach. However, although it is known that naturally, the features must be more positive in happier contexts, it is worth emphasizing the need for a study in other contexts such as anxiety, schizophrenia, bipolarity in order to verify differences and correlations between the patterns.

7.2 Future Work

We envision the main future works:

- Develop a Web and Mobile solution that analyzes the behavior patterns of online users since they consensually opted to log in and share their data. A trusted specialist could provide this tool.
- Explore emotional patterns using online learning or never end learning to improve the intelligent model continuously.
- Explore the solution proposed in this thesis in (i) other mental health contexts, such as anxiety, burn-out, bipolarity, and schizophrenia, and (ii) other platforms using smartphones and wearables.
- Develop a model that evaluates differences in semantic spaces of emotions to update the model proposed by Scherer (2005b) and evaluate other dimensions of emotion.

In the next section, we highlight the publications that originated during the doctorate and related to the thesis.

7.3 Publications:

The main publications that originated of this Thesis are:

- **(GIUNTINI *et al.*, 2019): GIUNTINI, FELIPE TALIAR**; RUIZ, LARISSA PIRES; KIRCHNER, LUZIANE DE FATIMA; PASSARELLI, DENISE APARECIDA ; DOS REIS, MARIA DE JESUS DUTRA; CAMPBELL, ANDREW THOMAS; UEYAMA, JO . How do I feel? Identifying emotional expressions on Facebook reactions using clustering mechanism. IEEE Access, v. 7, pp. 53909-53921, 2019.
- **(GIUNTINI *et al.*, 2020): GIUNTINI, FELIPE T.**; CAZZOLATO, MIRELA T.; DOS REIS, MARIA DE JESUS DUTRA; CAMPBELL, ANDREW T.; TRAINA, AGMA J. M.; UEYAMA, JÓ . A review on recognizing depression in social networks: challenges and opportunities. Journal of Ambient Intelligence and Humanized Computing, v. 11, p. 4713-4729, 2020.
- **(GIUNTINI *et al.*, 2021a): GIUNTINI, FELIPE T.**; DE MORAES, Kauê L.;CAZZOLATO, MIRELA T.; KIRCHNER, L. de F.; DOS REIS, MARIA DE JESUS DUTRA ; CAMPBELL, ANDREW T. ; TRAINA, AGMA J. M. ; UEYAMA, JÓ. Modeling and assessing the temporal behavior of emotional and depressive user interactions on social networks. IEEE ACCESS, v.9, pp. 93182-93194, 2021.

- (GIUNTINI *et al.*, 2021b): **GIUNTINI, FELIPE T.**; DE MORAES, Kauê L.; CAZZOLATO, MIRELA T; DOS REIS, MARIA DE JESUS DUTRA; CAMPBELL, ANDREW T.;TRAINA, AGMA J. M.; UEYAMA, JÓ. Tracing the emotional roadmap of depressive users on social media through sequential pattern mining. *IEEE ACCESS, v.9, pp. 97621-97635, 2021.*

Complementary contributions:

- (GIUNTINI; UEYAMA, 2017): **GIUNTINI, F. T.**; UEYAMA, J.. Explorando a teoria de grafos e redes complexas na análise de estruturas de redes sociais: Um estudo de caso com a comunidade online Reddit. In: XIII WORKSHOP DE REDES P2P, DINÂMICAS, SOCIAIS E ORIENTADAS A CONTEÚDO (WP2P+), 2017, Belém-PA. Anais do Simpósio Brasileiro de Redes de Computadores (2017). Porto Alegre: Sociedade Brasileira de Computação (SBC), 2017. v. 13. p. 21-31.
- (CAZZOLATO *et al.*, 2019a): CAZZOLATO, M. T.;**GIUNTINI, F. T.**; RUIZ, L. P.; KIRCHNER, L. F.; PASSARELLI, D. A.; REIS, M. J. D.; TRAINA JUNIOR, C.; UEYAMA, J.; TRAINA, A. J. M.. Beyond Tears and Smiles with ReactSet: Records of Users? Emotions in Facebook Posts. In: 2o.Dataset Showcase Workshop (DSW-SBBD 2019) do 34 Simpósio Brasileiro de Banco de Dados, 2019, Fortaleza. DSW-SBBD, 2019, *(Best paper Award).*

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ANNEX

A

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