UNIVERSIDADE DE SÃO PAULO
FACULDADE DE FILOSOFIA, CIÊNCIAS E LETRAS DE RIBEIRÃO PRETO
DEPARTAMENTO DE COMPUTAÇÃO E MATEMÁTICA

AUGUSTO, PATRICIA BRUNIERO FRANCISCATO

Random Forest multiclasses: um estudo diagnóstico de dificuldades de aprendizagem matemática

Ribeirão Preto-SP

2024

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Versão Corrigida

Versão original encontra-se na FFCLRP/USP.

Dissertação apresentada à Faculdade de Filosofia, Ciências e Letras de Ribeirão Preto (FFCLRP) da Universidade de São Paulo (USP), como parte das exigências para a obtenção do título de Mestre em Ciências.

Área de Concentração: Computação Aplicada.

Orientador: Prof.Dr. Zhao Liang

Ribeirão Preto-SP

2024

AUGUSTO, PATRICIA BRUNIERO FRANCISCATO

Random Forest multiclasse : a diagnostic study of mathematical learning difficulties

Corrected Version

The original version is found at FFCLRP/USP.

Dissertation presented to Faculdade de Filosofia, Ciências e Letras de Ribeirão Preto (FFCLRP) from the Universidade de São Paulo (USP), as part of the requirements to hold the Master of Science degree.

Field of Study: Applied Computing.

Supervisor: Prof.Dr. Zhao Liang

Ribeirão Preto-SP

2024

Augusto, Patricia Bruniero Franciscato
Random Forest Multiclasses: um estudo diagnóstico de dificuldades de aprendizagem matemática. Ribeirão Preto, 2024.
232 p. : il. ; 30 cm

Dissertação de Mestrado, apresentada à Faculdade de Filosofia, Ciências e Letras de Ribeirão Preto/USP.
Área de concentração: Computação Aplicada.
Orientador: Zhao Liang.

1. Random Forest. 2. Dyscalculia. 3. Learning Disability.

Augusto, Patricia Bruniero Franciscato

Random Forest multiclasses: um estudo diagnóstico de dificuldades de aprendizagem matemática

Master Degree Dissertation presented to the Department of Mathematics and Computing Science, University of São Paulo .

Approved dissertation. Ribeirão Preto-SP, January, 11th 2024:

Orientador:
Prof. Dr. Zhao Liang

Professor
Prof. Dr. Murillo Guimarães Carneiro

Professor
Prof. Dr. Vitor Geraldi Haase

Ribeirão Preto-SP
2024

This work is dedicated to all mothers, heroines in their homes, fighters for their families and their children. To the mothers who multiply themselves in daily activities, who build inexplicable relationships of affection, which are the basis of their home, but who never stop dreaming, believing that they are capable of, in addition to the glory of motherhood, still realizing personal dreams and desires to collaborate.

Acknowledges

First and above of all I thank God, for the opportunity of life and for daily miracles that enabled me to get here.
I am grateful to Professor Dr. Zhao Liang, for the opportunity, for his endless patience and kind orientation during whole master period.
I do thank my family, specially my husband Renato and my kids Rebecca and Giovani, for the support and for understanding the absent hours.
My thanks for my mother Neusa that ever inspired me with her strength for living.
I also thank to MSc. Giulia Paiva, from UFMG, for sharing her experience, work and knowledge without what this work could not be done.
A special thank for Professor Dr.José Augusto Baranauskas, for all orientation and corrections that improved my work and comprehension.
I would also like to thank Professor Dr.Vitor Geraldi Haase, from UFMG, for leading me to Giulia, becoming possible the partnership for this work, and therefore for all background transferred by publications I have read.
Futhermore, I would like to thank Professor Dr. Galera from Psicobiology Departament - USP, who was responsible to connect me to UFMG colleagues.
I kindly thank for docent group from DCM - USP who taught and lead me to new concepts and a whole new world of opportunities. I also thanks for all staff support.
I would like to thank my English advisor Thacia Carpenter who made me believe I could write this work by myself.
I thank for the Center for Artificial Intelligence (C4AI-USP), with support by the São Paulo Research Foundation and by the IBM Corporation, that carried out this work.
At last, but not least, I wish to thank everyone who believed this work was possible, and also to those who doubted it, anyhow I felt motivated and meant a lot to me.
. . .

Do not conform to the pattern of this world,
but be transformed by the renewing of your mind.
Then you will be able to test and approve what
God's will is—His good, pleasing and perfect will.
(Holly Bible , Romans 12:2)

Abstract

Random Forest multiclasses: um estudo diagnóstico de dificuldades de aprendizagem matemática

Os transtornos específicos de aprendizagem (TEA) têm origem neurobiológica e são classificados de acordo com seus domínios específicos. A discalculia do desenvolvimento (DD) é uma TEA com comprometimentos acadêmicos persistentes nas habilidades matemáticas referentes ao sentido numérico, memorização de fatos aritméticos, desempenho ou fluência de cálculos e raciocínio matemático.

O desenvolvimento de mecanismos diagnósticos eficientes para Discalculia do Desenvolvimento (DD) utilizando técnicas de aprendizado de máquina tem ganhado atenção significativa em pesquisas recentes. Convencionalmente, o diagnóstico da DD envolve processos demorados, incluindo múltiplos exames e entrevistas que se estendem por semanas ou meses. Entretanto, estudos recentes têm demonstrado o potencial de gerar modelos classificadores com alta acurácia utilizando instrumentos psicométricos, que podem contribuir para a redução da complexidade do processo diagnóstico.

Esta pesquisa apresenta um método estruturado cujo objetivo é identificar oportunidades para o protocolo do Ambulatório NUMERO, utilizando Random Forest para análise de classificação e importância de variáveis. Partindo da redução de dimensionalidade, por meio de um método híbrido combinando agrupamento hierárquico e classificação de RF, propusemos eliminar variáveis irrelevantes e, consequentemente, melhorar amplamente a eficiência do classificador. Simulações computacionais apresentam resultados promissores em muitas versões de conjuntos de dados.

A abordagem proposta tem grande potencial para suportar eficientemente o diagnóstico de discalculia do desenvolvimento, oferecendo uma valiosa contribuição para o campo da avaliação e intervenção cognitiva, além de ser adaptável a demais diagnósticos que se baseiem em psicometria.

Palavras-chave: Random Forest, discalculia, matemática, dificuldade de aprendizagem, diagnóstico, psicometria.

Abstract

Random Forest multiclasses: a diagnostic study of mathematical learning difficulties

Specific learning disorders (SLD) have a neurobiological origin and are classified according to their specific domains. Developmental dyscalculia (DD) is a SLD with persistent academic impairments in mathematical skills regarding numerical sense, memorization of arithmetic facts, performance or fluency of calculations and mathematical reasoning.

The development of efficient diagnostic mechanisms for DD using machine learning techniques has gained significant attention in recent research. Conventionally, the diagnosis of DD involves time-consuming processes, including multiple tests and interviews that extend over weeks or months. However, recent studies have demonstrated the potential for generating classifier models with high performances using psychometric instruments, which can contribute to reducing the complexity of the diagnostic process.

This research presents a framework to identify opportunities to the NUMERO Outpatient Clinic protocol using Random Forest for classification and variable ranking analyses. Applying a dimensionality reduction mechanism, a hybrid method combining hierarchical clustering and RF classification, we proposed to eliminate irrelevant variables and, consequently, largely improve model's efficiency. Computer simulations present promising results throughout many dataset versions.

Our approach holds great potential for efficiently support diagnosing developmental dyscalculia, offering a valuable contribution to the field of cognitive assessment and intervention, while may also be adapted to another psychometric based diagnose.

Keywords: Random Forest, dyscalculia, mathematics, learning disability, diagnosis, psychometrics.

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List of Acronyms

.

[DD] Developmental Dyscalculia

[ASD] Specific Learning Disorder

[ADHD] Attention Deficit Hyperactivity Disorder

[MLD] Mathematical Learning Disability

[MD] Mathematical Difficulties

[EFES] Exploratory Family Interview

[TDE] School Performance Test

[RCPM] Raven's Colored Progressive Matrix

[WAIS] Wechsler Adult Intelligence Scale

[RF] Random Forest

[ROC] Receiver Operating Curve

[HCA] Hierarchical Cluster Algorithm

[KNN] K-Nearest Neighbor

[CART] Classification and Regression Tree

[LTU] Linear Threshold Unit

[BRRF] Binary Relevance Random Forest

[RFLP] Random Forest Label Power-Set

[RF-PCT]Random Forest of Predictive Clustering Trees

[UFMG] Federal University of Minas Gerais

[AUC] Area Under Curve

[FWER] Family-Wise Error Rate

[PICO] Population, Intervention, Comparison and Outcomes

[FURIA] Fuzzy Unordered Rules Induction Algorithm

[WJT] Woodcock-Johnson Test

[SVM] Support Vector Machine

[CONEP] National Council Research

[LND] NUMERO Outpatient Clinic

[MODT] Multi-Objective Decision Tree

[CD] Critical Distance

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Introduction

1.1 Background

Developmental Dyscalculia is currently defined as an irreversible disorder, having an important impact on the social condition of its carriers, given the great relevance of arithmetic knowledge for daily life skills. Commonly diagnosed after early school life, they are characterized by persistent learning difficulties (APA, 2018).The prevalence of DD is 3% to 6% of school-age children(HAASE; COSTA; MICHELI, 2011).

The diagnosis of developmental dyscalculia is clinical (WEISS, 2020)(HABERSTROH; SCHULTE-KORNE, 2019)(HAASE; COSTA; MICHELI, 2011), i.e., there are no well-established biological markers today (APA, 2018), and differential, being disregarded diagnoses resulting from brain traumas (paralysis, epilepsy), neuro-genetic diseases (Turner syndrome, X-fragile), visual and hearing difficulties, low intellectual level (IQ<70), emotional diseases (anxiety, phobias) and issues of social origin (inadequate schooling, poverty, family conflicts) (APA, 2018; HABERSTROH; SCHULTE-KORNE, 2019). The incidence of comorbidity of DD, especially with dyslexia and attention deficit hyperactivity disorder (ADHD) is significant (KAUFMANN; ASTER, 2012)(PETERS et al., 2018).

Besides DD, mathematical learning disability (MLD), non-verbal disorder (NVLD) and mathematical difficulties (MD) are also associated to arithmetic learning deficits, related to impairments in cognitive functions as phonological, working memory and visuospatial abilities. The high heterogeneity is associated to diagnosis complexity, while symptoms and some characteristics are shared by all disorders. Furthermore, some genetic syndromes manifests impairments in mathematics and deficits in other cognitive deficits as phonological processing and working memory. Dyscalculia persists into adulthood, compromising behavioral, occupational, and academic issues. Limitations of employ-ability and professional performance are also associated with dyscalculia. Internalizing and externalizing psychopathology may also be associated with the persistence of learning difficulties in mathematics in adolescence (HAASE; COSTA; MICHELI, 2011; HABERSTROH; SCHULTE-KORNE, 2019; KAUFMANN; ASTER, 2012; AUERBACH et al., 2008; HAASE et al., 2012; PAIVA, 2021).

The accepted diagnosis process of DD requires the execution of several evaluations, including interviews with family members and teachers, psychometric tests, specific learning tests, neurocognitive assessment, neurodevelopment and neurological evaluation, imaging tests, among others. The selection of individually applied tests is made based on the hypotheses established by the professional, considering the complaint posed, the data from anamnesis and exploratory family interview (EFES). The diagnosis, however, is not restricted to the psychometric survey (WEISS, 2020; HABERSTROH; SCHULTE-KORNE, 2019; PAIVA, 2021; MAMMARELLA et al., 2021), but on the other hand, due to the absence of specific cognitive and biological markers, the diagnosis of DD depends on the use of psychometric tests(SILVA et al., 2020).

Among the psychometric tests used in the diagnosis of mathematics difficulties are the TDE (School Performance Test), Raven's Colored Progressive Matrices (RCPM), Simple Calculation Task, Arabic Numeral Writing, Woodcock-Johnson IV and TEDI Math Grands as well as neuropsychological tests to evaluate other cognitive functions such as verbal and non-verbal IQ (intelligence quotient) assessment with WAIS subtests (Wechsler Adult Intelligence Scale), evaluation of the verbal component of working memory with the 'digit span' (measures short-term auditory memory and attention) and evaluation of visual spatial working memory, with Corsi Blocks.(PAIVA, 2021; SILVA et al., 2020; CASTALDI et al., 2018).

1.2 Motivation and Objectives

The techniques and evaluations currently available make the diagnosis of DD a long and individualized process. Accelerating the process of carrying out the diagnosis of dyscalculia and making it accessible to the population of early childhood and elementary education is essential for interventions to be carried out in a timely manner, aiming to reduce social and economic impacts.

Performing an early diagnosis followed by referral to a multidisciplinary team can bring positive results for the child with Developmental Dyscalculia(HAASE; COSTA; MICHELI, 2011).

The use of machine learning techniques applied to psychometric data can contribute to accelerate the diagnostic process and possibly reposition the diagnosis, currently exclusive to the clinical environment. The definition of the approach is the current differential between the various studies identified, as the application of machine learning to predict dyslexia, for example (ORLEANS et al., 2016; MARIMUTHU; SHIVAPPRIYA; SAROJA, 2021; KAISAR, 2020). Studies applied to DD are more recent compared to other learning disabilities and still available in smaller numbers (HAASE; COSTA; MICHELI, 2011).

In our research we found that Geary suggests three sub-types of mathematical difficulties, namely, procedural sub-type, sub-type related to semantic memory and visuospatial sub-type (GEARY, 2004). Haase (2011) reports that investigations for the problem of comorbidity propose the concept of endophenotypes, which correspond to the intermediate steps of environmental regulation and self-regulation, in the structure that extends from genotype to phenotype (HAASE; COSTA; MICHELI, 2011) and Silva and other researchers consider that an assessment based on the sub-components of numerical cognition processing may be more effective for identifying specific impairment profiles (SILVA et al., 2020).

In another approach, recent study by Mammarella et.al. (2021) indicates that there are no specific deficiencies to justify the mathematical learning disabilities (MLD) and DD, and a dimensional approach is necessary. That shows that patients with MLD and DD have small diagnosis variations over a dimensional space and different deficiencies may vary due to comorbidity, severity of cognitive disorder, age, among other factors(MAMMARELLA et al., 2021).

In our interpretation, considering the suggested dimensional approach, the diagnosis process of mathematical learning disabilities can be described as a problem of multiple classification with high dimensional data. The complexity of the diagnosis of dyscalculia and inherent comorbidity, such as dyslexia and ADHD, suggests a great possibility of contribution from machine learning techniques to analyze data in the search for an effective classification modelings.

The main objective of this work was to evaluate possible classification models resulting from the application of combined methods of supervised machine learning, based on the Random Forest method. To do so, we used NUMERO Outpatient Protocol, a specialized protocol for developmental dyscalculia and comorbidity diagnosis. The Outpatient Clinic specializes in the evaluation and rehabilitation of children and adolescents with mathematical learning difficulties and genetic syndromes.

More specifically, we propose a multiclass framework to enhance the diagnostic efficiency of DD and comorbidity. Beginning with dimensionality reduction analysis, we combine a hierarchical cluster threshold selection with RF performance metrics criteria, based on ROC curve analysis. Finally, we create an interactive model selection through statistics tests (Friedman, Wilcoxon and Bonferroni-Dunn), and we obtained a valid framework to generate a multiclass classifier for diagnosing learning disorders, built over psychometric protocols. We complementary deliver a variable rank from two different methods, both based on RF tools.

Nevertheless, a noticeable premise of this dissertation is that no algorithm changing is part of our purpose. That means, we managed data and chosen algorithms combination to fit the solution planned, although this limitation imposed some specific characteristics to missing value treatment, for example.

1.3 Organization

This document is organized into five five chapters and appendixes:

- In Chapter 2, we introduce the fundamentals of supervised machine learning techniques implemented in the project, specially Random Forest tools, related metrics and statistical tests. Complementary, we present a systematic mapping carried out with the objective of understanding the state of the art regarding the application of machine learning techniques for the diagnosis of learning difficulties, specifically dyscalculia.
- In Chapter 3, we present the framework in the methodology section, bringing the premises, criteria, characteristics and parameters for developing the framework.
- In Chapter 4, we present the results obtained so far, beginning with concepts and filters used to compose the data set versions. We bring forWard a complexity analysis and a comparison between two different methods for missing values treatment. We also justify the choice of the Random Forest method and address the characteristics of our approach.
- In Chapter 5, we present comments and conclusions, based on the knowledge acquired up to the time of editing this dissertation document.
- In Appendix A, we present all applied packages and tools to generate the framework within Python environment.
- In Appendix B, we discuss in detail some basic knowledge.
- In Appendix C, we explain the Outpatient protocol from UFMG Laboratories, its flow processes, and instruments.
- In Appendix D, we discuss some intermediate results.
- In Appendix E, we present the main algorithms developed during the project.
- In Appendix F, all plots and figures of complementary results are presented.

2

Theoretical Reference

2.1 Machine Learning

Machine learning is the result of the interdisciplinary union of statistics and applied computing to solve a series of problems based on data sets or experience. It happens that for the solution of some types of problems, the elaboration of an algorithm built step-by-step is not feasible due to its complexity. In these cases, the machine learning algorithm analyses a particular data set and elaborates a model that describes the behavior of the data. In the process of learning, or training the algorithm, values of the parameters of the model are determined that minimize its error function, with the aim of improving its performance and predictive capacity.

The observed data set is partitioned between training, validation and test. Depending on the dimensional complexity and size of the data set, one may consider applying dimensional reduction techniques. Machine learning algorithms are typically classified into supervised, unsupervised and reinforcement learning, depending on their application and available data (ALPAYDIN, 2011). Generally, we can say that a supervised method is applicable when there is data for training the algorithm both input and output, that it is unsupervised when there is only input training data, and that it is reinforcement learning when there is no data for training, which are generated from attempts and actions performed in each environment. Different types of machine learning algorithms result in different models and have different error functions.

2.2 Unsupervised Machine Learning

The training set $X = \{x^t\}_{t=1}^{N}$, n = number of examples and t = time, has only one set of variables drawn from some unknown probability density $x^t \approx p(x)$ and the aim is to estimate it using a model with θ parameters $x^t \approx q(x|\theta)$.

We want to find θ that makes $q \approx p$, that maximizes the probability of drawing the sample (maximum likelihood estimation), based on similarities or dissimilarities.

In this dissertation, we have applied unsupervised machine learning technique during pre-processing step, more specifically, Hierarchical Cluster Algorithm (HCA) as part of our proposal for a hybrid feature selection.

Clustering analysis is a widely known method of unsupervised machine learning. Hierarchical Clustering Algorithm (HCA) may be described as a multi-scale version of clustering analysis. Clustering formatting is similarly based on the minor distance and it aims to produce a set of clusters as well as the hierarchical relationship between them. The agglomerative approach used here is a bottom-up procedure. Starting with each variable in its own cluster, merge the two closest clusters, until only one remains up the hierarchy. This tree-based relationship can be demonstrated visually with dendrogram and to determine the cluster is mandatory to establish a threshold cut on HCA levels. Hence, a given variable may belong to more than one cluster, as long as these clusters are related and the membership occurs at different levels.

Be U and V two formed clusters, where $u \in U,\ v \in V$, the following linkage methods describe some distinguish distance calculating formulas that can be used on a HCA application:

- Single linkage

$$d(U,V) = \min\ ||\ u - \ v\ || \tag{2.1}$$

- Complete linkage

$$d(U,V) = \max\ ||\ u - \ v\ || \tag{2.2}$$

- Distance between clusters centers

$$d(U,V) = \ ||\ mean(u) - \ mean(v)\ || \tag{2.3}$$

- Ward´s method ($|\cdot|$ is the cardinality)

$$Ward(U,V) = \frac{|U| * |V|}{|U| + |V|}\ ||\ mean(u) - \ mean(v)\ ||^2 \tag{2.4}$$

Here we perform hierarchical clustering algorithm (HCA) over features' Spearman rank-order correlation matrix (AL., 2011). We obtain Spearman correlation matrix for all variables and a cluster hierarchy linkage is performed, with Ward method option, over the correlation matrix, forming clusters that minimizes the total within-cluster variance. Spearman correlation in better explained on Appendix B.

2.3 Supervised Machine Learning and Classification

Let be a set of observed data $X = \{x^t, r^t\}_{t=1}^N$, where n is the number of examples and t is the time, and $r^t = f(x^t, z^t)$, where f is an unknown function and z an unobservant variable. The goal of modeling is to find $y^t = g\,(x^t|\theta)$ that brings it as close as possible $y^t = r^t$, where g is the model and θ are the parameters of that model, learned during training(ALPAYDIN, 2011).

The error function of a supervised machine learning method measures the deviation between the y^t prediction and the expected result r^t. In this case, the error function can be described in terms of a loss function L as

$$err(g) = arg\,min_\theta \sum_t L\,(r^t, y^t) = arg\,min_\theta \sum_t L\,(r^t, g\,(x^t|\theta)) \tag{2.5}$$

Through the obtained model, one can predict a result from new input data. If the result is a category, the problem is termed as classification. If the result is numeric, the problem is described as regression.

Typically, in a classification problem you have the training data set

$$R = \{(X_1, Y_1), (X_2, Y_2), \ldots, (X_m, Y_m)\},$$

of m examples where $X = x_1, ...x_n$ is the set of dimension n of applicable variables, and Y is the set of classes or categories. It is to build a model that, given a new element X, is able to predict Y.

In the linear discriminate approach, considering that the diagnostic problem is binary ($q = 2$), where q is the number of classes, the definition sufficient for the discriminant function g is

$$g(x|w\,|w_0 = w^t x + w_0), \tag{2.6}$$

The separation between classes $(C1, C2)$ is a hyperplane and the classification is

$$C1\ , if\ \ g(x|w\,w_0) > 0,\ otherwise\ C2.$$

The g-model is the discriminating function of the classification, and the error function is given by a zero-one loss function whose purpose is to minimize classification errors.

2.3.1 K-Nearest Neighbor (KNN)

Neighbors-based classification is a type of example-based learning or non-generalizing learning: it does not attempt to construct a general internal model, but simply stores examples of the training data.

As a supervised method, the principle behind KNN is to find a predefined number of training samples closest in distance to the new point and predict the label from these. The number of samples can be a user-defined constant (k-nearest neighbor learning) and the distance measure is usually Euclidean distance.(HOLMES; ADAMS, 2002). Despite its simplicity, this non-parametric method has been successful in many classification and regression problems, often used in classification situations where the decision boundary is very irregular.

In this dissertation, K-Nearest Neighbors approach is utilized in imputation process where an Euclidean distance metric that supports missing values is used to find the nearest neighbors. Each sample's missing values are imputed using the mean value from nearest neighbors found in the training set. Two samples are considered close if the features that neither is missing are close.

2.3.2 Decision Tree

Decision Tree is a method of discriminate, flexible approach, whose complexity is determined as a function of the training data set (ALPAYDIN, 2011). It can be applied to any type of data (numerical and categorical), any number of classes and different volumes of data and still holds the characteristic of interpret ability, as the tree may be written as a set of if-then rules, allowing knowledge extraction (LOH, 2014).

An important theme in the application of decision trees is the adjustment or overfitting of the model to the training data, to the detriment of its predictive capacity. The determination of the time of pruning is important to avoid over adjustment and common strategies consider stopping when the result is pure enough, when the tree reaches a certain size or perform a pruning after the construction of the tree using validation data (LOH, 2010).

Certain types of splits can be produced until the sample space is partitioned into regions that contain only samples of a single class, other types of splits have inherent stop rules that would not allow such a complete partition. In the Gini impurity index used in the CART algorithm and in the entropy function, in C4.5, the nodes resulting from a new division are evaluated in order to obtain the minimization of the impurity or the maximization of the gain rate respectively (GEHRKE, 2011; BRODLEY; UTGOFF,

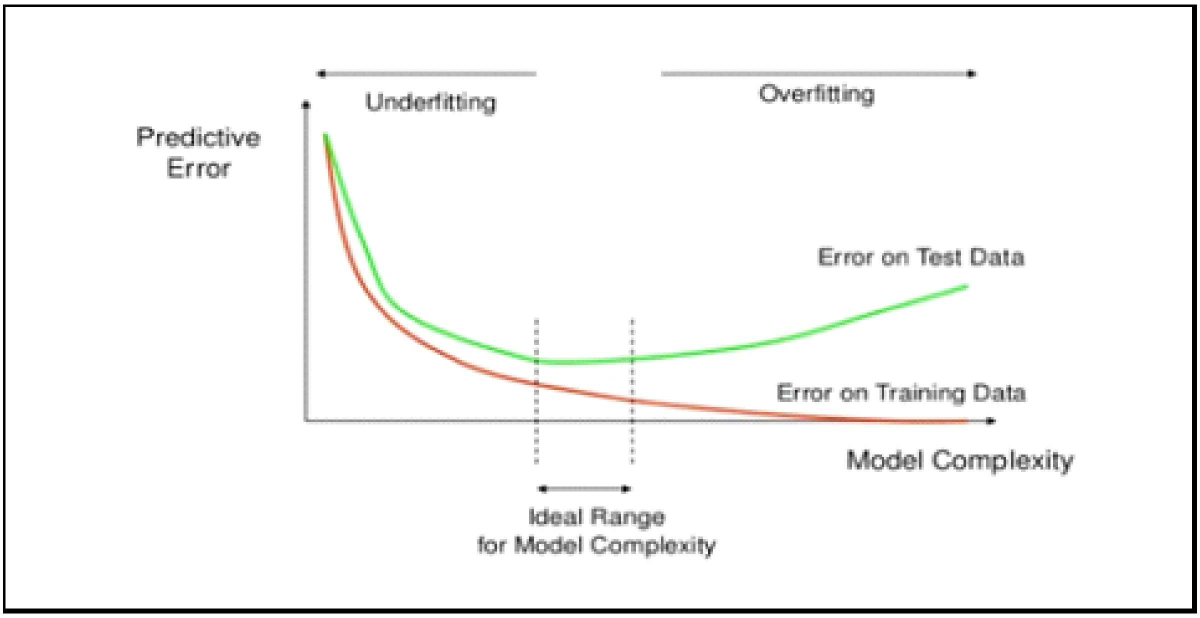

Figure 1 – Fonte (AL-BEHADILI; KU-MAHAMUD; SAGBAN, 2018) Efeitos do Overfitting e Underfitting

1995).

A stop criterion can also be artificially introduced in any type of split, for example by limiting the number of levels of the tree. Another approach is to build a fully split tree and then prune retroactively. In the case of multivariate decision trees, there is the possibility of using LTU (linear threshold unit), binary test with established limit, or LM (linear machine), a set of discriminant linear functions for division of nodes. (BRODLEY; UTGOFF, 1995; UTGO; BRODLEY, 1991).

Decision trees are algorithms that are considered unstable, meaning that small variations in training data can cause large changes to the resulting models. One can weight the training data of the algorithm (boosting by weighting) and increase the importance of data considered classification errors. This process of boosting decision trees reduces the classification error and requires serial execution: it is necessary to finish the construction of a tree and then build a new one based on the previous classification errors.

In some contexts, where the goal is classification into multiple categories or classes, the simplified approach is built with the generation of binary models (single output model) for each class analyzed, distinctly. Alternatively, the decision tree method allows you to build a unique multiclass model, based on multi output model, whose main benefit is that the dependency between variables can be considered in the model(KOCEV et al., 2007; CHAUDHARY; KOLHE; KAMAL, 2016; LOUPPE, 2014).

Issues such as selection and reduction of variables, missing data treatment strategy and relationship between sample size and its dimensionality influence the classification capacity and effectiveness of the application of the method (BRODLEY; UTGOFF, 1995).

2.3.3 Random Forest

Random Forest (RF) is an ensemble machine learning method, in which a set of decision trees is constructed based on the random selection of bootstrap aggregation or bagging data and the final classification is obtained by the majority vote of the trees produced (BREIMAN, 1996; BREIMAN, 2001) or categories and functions in more complex cases (HO; HULL; SRIHARI, 1994).

Bagging is especially efficient when applied to a sample with noise (DIETTERICH, 1995). For each sample in the set, a record of the test data set has the probability 1-(1-1/B) B of being selected at least once, in B times the records are randomly selected. If B is large, this equates to approximately 1 - 1/e = 63.2%, which is to say that each sample generated contains only 63.2% of unique variables from the training dataset. This disturbance provides opportunities for the creation of different trees, due to their characteristic of instability, and their performance may improve if the trees are not correlated.

In RF method, the trees are developed to their maximum depth and this set of trees can be built in parallel processing. These characteristics ensure that the trees produced are necessarily different from each other, with low risk of over-fitting, while enabling the application of RF to data sets with high dimensionality (BREIMAN, 2001; BREIMAN, 2004). In this way, however, the interpret ability of the results previously guaranteed by the decision trees, in the forest, ends up being impaired. In this context, an important characteristic of RF is the possibility of analyzing the importance of variables regarding predictive capacity (BREIMAN; CUTLER, 2004). The permutation importance measure in RF is based on decreased predictive performance when the values of a descriptive variable in a node of a tree are randomly exchanged.

A second component of randomization in RF (sub bagging) selects a subgroup of attributes, defined by the variable *mtry*, for the division of nodes and calculation of the Gini index, observing *mtry´m*, where *mtry* is the number of randomly selected attributes and m the number of variables (RF-RI). It is also possible to use linear combinations of variables, ensuring the strength of the model, without compromising in terms of correlation of variables (RF-RC) (BREIMAN, 2004).

In the RF, the classification error is estimated during the training using the data not selected in the sample, for specific construction of each tree, as a validation dataset (out-of-bag) (BREIMAN; CUTLER, 2004). In classification, prediction performance can be quantified in terms of the rate at which OOB sampling incurs errors across multiple classifiers. This allows the RF model to be suitable and validated while it is trained.

An important aspect of our use of RF in this dissertation is that scikit-learn uses an optimized version of the CART algorithm, however, the scikit-learn implementation does not support categorical variables for now (AL., 2011).

2.3.4 Multiple Classification

There are many applications in the real world where an example is associated with several categories simultaneously and there is dependence or structural relationships between classes, such as in cases of medical diagnosis involving comorbidity (ZUFFEREY et al., 2015), identification of genetic markers, applications in the area of ecology, multimedia and categorization of texts (KOCEV et al., 2013). Classification problems can associate a single class with each record or example (single label), or the same example can be associated with one or more classes (multi label).

From the point of view of execution, sorting can be performed in binary pairs (single objective) or directly in multiple classes (multi objective). The variation in the characteristics of the solution implies its algorithmic complexity, applicable metrics, generalization capacity, degree of correlation analyzed, and specific limitations. More details at (ZHANG; ZHOU, 2014).

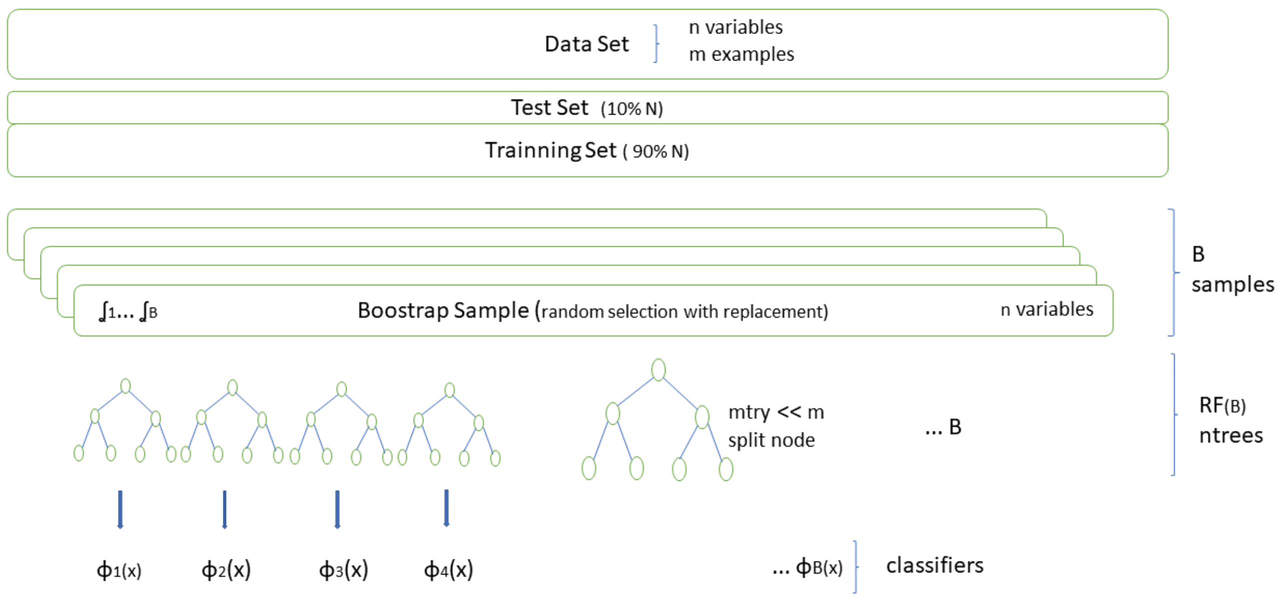

Figure 2 – Random Forest Strategy : beginning with a data set with n variables and m examples, we split into training and test dataset. From training set, over a random selection of variables with replacement, a number of decision trees (DT) is built to compose the forest. As result, each binary DT of the forest determines a probability of one single class (one-vers-rest). The process repeatedly considers each one of the possible classes.

The choice of the Random Forest method for data classification was driven by the hierarchical characteristic of the construction of the NUMERO Outpatient Clinic protocol, as well as the diversity of data types. The protocol is detailed in Appendix C. In addition to its simplicity, the RF method is recognized for its good performance and ability to adapt to samples of small size and high dimensionality of variables and complexity of data structure (SCORNET; BIAU; VERT, 2015). Another important feature is that the decision tree classifier, the basis of the RF method, is widely used in applications in the diagnostic field of medicine (JENA; DEHURI, 2020).

2.3.5 Importance of Variable Analysis

In most machine learning tasks, the goal is not only to find the most accurate model of the answer, but also to identify which of the variables are the most important to make the predictions, for example, to lead to a deeper understanding of the problem under study.

Furthermore, in classification processes, to identify the relevance of each variable is an important task. In this dissertation it is raised to a fundamental issue, since through this analysis we may increase knowledge of disorders diagnosis and core cognitive competences involved. However, prior to inspecting the feature importance, it is important to check that the model predictive performance is high enough. Indeed, there would be little interest of inspecting the important features of non-effective predictive model.

In this context, RF offers several mechanisms to assess the importance of an input variable and, therefore, increase the interpret of the model. Here we employ two different mechanisms to evaluate the importance of selected variables to the best accurate RF models classification, for each diagnosis class: the native RF importance of variable and the permutation importance mechanism.

2.3.5.1 Random Forest Importance of Variable

As more complex the RF becomes, the interpret ability of the results in the forest diminishes. In this context, an important characteristic of RF is the possibility of analyzing the importance of the variables in terms of predictive capacity (BREIMAN; CUTLER, 2004). While developing the forest, at each node split of trees, RF method selects one variable according to minor Gini Index G, which is calculated by subtracting the sum of the squared probabilities p of each class $j = (1, 2... q)$ from one, as follows:

$$G = 1 - \sum_{j=1}^{q} {p_j}^2 \tag{2.7}$$

Due the upper mentioned mechanism, the impurity-based importance is called native to RF. It is known to be influenced toWards high cardinality features, where a numerous options of values for a variable can make it more important to reduce the impurity split, even it does not mean importance to predict. It shall be observed during RF importance result analysis.

Here we implemented the scikit-learn mechanism, that uses an optimized version of the CART algorithm with default criterion (gini) that constructs binary trees using the feature and threshold that yield the largest information gain at each node. Therefore, complementary we implemented the permutation importance where the cardinality does not impact the importance of a variable.

2.3.5.2 Permutation Importance

The permutation importance measure in RF is based on decreased predictive performance when the values of a descriptive variable in a node of a tree are randomly exchanged. Permutation importance does not reflect to the intrinsic predictive value of a variable by itself but how important this feature is for a particular model. In this context, the greater the model performance the more reliable is the importance obtained.

2.4 Metrics and Statistical Tests

In this section we discuss metrics and statistical tests of our framework.

2.4.1 ROC Curve and Area Under Curve (AUC)

The ROC (receiver operating characteristics) curve is a statistical tool widely used to analyze the predictability of a model. Considering a discrete and binary classification model (k=2), where the positive result is P and the negative is N, from the combination of predicted classes and actual classes we have the confusion matrix:

Table 1 – Confusion Matrix

Predicted Class	Actual Class Positive	Actual Class Negative	Row Total
Positive	TP	FP	TP+FP
Negative	FN	TN	FN+TN
Column Total	TP+FN	FP+TN	TP+FP+FN+TN

- TP = Number of true positive results
- TP = Number of true positive results
- FP = Number of false positive results
- TN = Number of true negative results
- FN = Number of false negative results
- TP + FN = Number of all positive results
- FP + TN = Number of all negative results
- TP + TN = Number of all correct predictions
- FP + FN = Number of all wrong predictions
- TP + FP + FN + TN = Number of all results

The terms of Table 1 are used to define the following metrics:

$$Sensitivity = TPR\ (TruePositiveRate) = \frac{TP}{TP + FN} \tag{2.8}$$

$$Specificity = TNR\ (TrueNegativeRate) = \frac{TN}{FP + TN} \tag{2.9}$$

$$Accuracy = \frac{TN + TP}{TP + FP + FN + TN} \tag{2.10}$$

$$FPR\ (FalsePositiveRate) = \frac{FP}{FP + TN} = (1 - specificity) \tag{2.11}$$

$$PPV\ (FalsePositiveRate) = \frac{FP}{FP + TN} = (1 - specificity) \tag{2.12}$$

Applicable to binary classification problems, common in disease diagnoses, it is obtained through the graphical representation of the sensitivity index versus the complement index of the specificity of the model. The ROC curve is very useful for performance comparison between models, however, for some specific conditions, the Precision-Recall curve is used (FAWCETT, 2006).

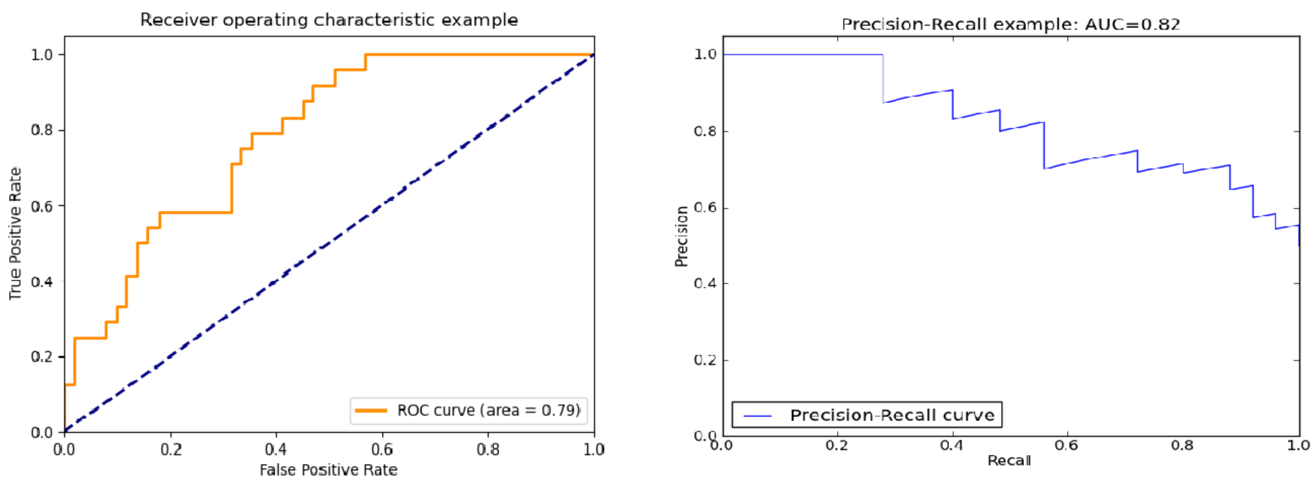

Figure 3 – ROC and Precision-Recall curve examples. Fonte (AL., 2011)

The closer the curve is to the upper left corner, the greater the performance of the test. The dotted line represents random classification curve, where a classification model is unnecessary or considered weak.

Commonly used, the area under ROC curve (AUC) provides a way to measure the performance of a classification model. The larger the area, the more accurate the model is. AUC of ROC curve can be measured by the following equation, where t = (1 – specificity) and ROC (t) is sensitivity.

$$AUC = \int_0^1 ROC(t)\, dt \tag{2.13}$$

ROC curve is also functional for multiclass classifiers, where for each specific class, an ROC curve is generated. Let C be a set of all classes, the ROC curve i presents the class c(i) as the positive class and all the others as negative.

We obtain the adequacy of the AUC metric by calculating the means applied to each class label individually in two ways: macro averaging and micro-averaging (TSOUMAKAS; VLAHAVAS, 2007).

For each y_j class label, the values $TP_j,\ FP_j,\ TN_j,\ and\ FN_j$ make up the confusion matrix with respect to the y_j element (ZHANG; ZHOU, 2014) and where B is a binary metric function $B(TP_j,\ FP_j,\ TN_j\ and\ FN_j)$:

$$Bmacro = \frac{1}{q}\sum_{j=1}^{q} B(TPj, FPj, TNj, FNj) \tag{2.14}$$

$$Bmicro = B(\sum_{j=1}^{q} TPj, \sum_{j=1}^{q} FPj, \sum_{j=1}^{q} TNj, \sum_{j=1}^{q} FNj) \tag{2.15}$$

In psychometrics as in medicine, the application of the ROC curve is widely used in the comparison of diagnostic performance between instruments and allows to study the variation of sensitivity and specificity for different cutoff values in the dimensional diagnostic approach (TRIPEPI et al., 2009; KRZANOWSKI; HAND, 2009; QI et al., 2018; ZHU; ZENG; WANG, 2010; BENFARES et al., 2021).

2.4.2 Complexity Analysis

In order to comprehend the impact of raw data set characteristics, some density metrics D_1, D_2, D_3 were calculated following density concept for machine learning techniques application as proposed by Oshiro (2012). Whether $D_i < 1$ the density is low and learning from this dataset should be difficult (OSHIRO; PEREZ; BARANAUSKAS, 2012). We also compute the dataset complexity ($|D| \times |L| \times |X|$) and $| \cdot |$ is the cardinality of its argument (READ; PFANHRINGER; HOLMES, 2011).

$$D_1 = log_n m \tag{2.16}$$

$$D_2 = log_n \frac{m}{q} \tag{2.17}$$

$$D_3 = log_n \frac{m+1}{q+1} \tag{2.18}$$

- m = the number of instances (mass)
- n = the number of variables (volume)
- q = the number of classes (q « m, commonly)

2.4.3 Statistical Tests

In this dissertation, we compare the performance of classifiers based on AUC metrics, over a small sample size. Since we consider a cross-validation mechanism, we use multiple comparisons and a family-wise-error-rate control procedure is relevant. The family-wise error rate (FWER) is defined as the probability of making at least one false rejection in a family of hypothesis-testing problems. Here we can have elevated probability of incorrectly identifying differences when no difference exists. Aware of that, we use Bonferroni correction in post-hoc tests, in which we reject all hypotheses for which $p - value <= \frac{\alpha}{h}$, where h is the number of hypotheses being tested and α is significance level of the test. For the tests implementation we follow Demsar (DEMšAR, 2006) recommendations to utilize Friedman, Wilcoxon and Bonferroni-Dunn tests. Although the power of tests may be weak, here we make a relative comparison between several classifiers instead of verifying the performance of models.

The implemented statistical tests from Scipy Stats(MAYOROV, 2020) are detailed on Appendix A.

2.4.3.1 Friedman Test

The Friedman test (FRIEDMAN, 1937) is a non-parametric statistical test of multiple group measures and uses the method of ranks to evaluate multiple values avoiding normality assumption. The null hypothesis states that whether the multiple group measures are equivalent they have same average ranks, to a certain required level of significance. On the other hand, whether the null hypothesis is rejected, their average ranks are not equal.

The Friedman test determines whether the rank total for each condition differ significantly from the values which would be expected by chance, assuming independence between events (one row´s example does not interfere with others) and each row can be possibly ranked independently, although examined results are obtained over same population or populations with same median(PEREIRA; AFONSO; MEDEIROS, 2015).

To perform comparative analysis between algorithms scores, we calculate the average ranks of those algorithms scores, based on multiple re-sampling from each data set, without any risk, since there is no bias expected on scores.(DEMšAR, 2006). Be r_i^j the rank of j^{th} of k algorithms on i^{th} of T data sets, we obtain R_j :

$$R_j = \frac{1}{T} \sum_i r_i^j \tag{2.19}$$

If the null-hypothesis is rejected, we can proceed with a post-hoc test to identify exactly which groups differ from each other.

2.4.3.2 Wilcoxon Test

During the comparison process of classifiers proposed here, it is possible to arrive at a point where only two classifiers are compared. In that exceptional case, the Wilcoxon test must be utilized since Friedman is adequate for more than three classifiers.

The Wilcoxon signed-rank test (WILCOXON; CYANAMID, 1945; HODGES; LEHMANN, 2012) is frequently described as the non-parametric equivalent of the paired t-test. In the case of the paired comparisons, rank numbers are assigned to the differences in order of magnitude ignoring signs, and then those rank numbers which correspond to negative differences receive a negative sign. This is necessary in order that negative differences shall be represented by negative rank numbers, and in order that the magnitude of the rank assigned shall correspond fairly well with the magnitude of the difference. It will be recalled that in working with paired differences, the null hypothesis is that we are dealing with a sample of positive and negative differences normally distributed about zero.

To interpret Wilcoxon results, most books on general statistics include a table with exact critical values for the minimum difference value between positive and negative ranks, for up to 25 data sets involved in comparison, related to a specific significance (generally alpha = 0.05). Here we implemented the algorithm provided by SciPy, better described on Appendix A.

2.4.3.3 Post-hoc Bonferroni-Dunn Test

When the null-hypothesis of Friedman or Wilcoxon is rejected, we proceed with a post-hoc test. In this dissertation maters compare all classifiers to a control (best averaged ranked one), so the Bonferroni-Dunn test is applied.

With Bonferroni test we reduce family-wise error rate (FWER), controlling the probability of type error 1 (false positive), when α is divided by the number of comparisons being made $k-1$ to obtain a conservative value of significance α_{new}. Meanwhile we keep lower the number of comparisons made. The less comparisons, less chance of error type 2 (false negative) to occur by chance.

The performance of two classifiers is significantly different if the difference between their respective average ranks surpass the critical distance (CD) :

$$CD = p_{\alpha_{new}} \sqrt{\frac{k(k+1)}{6c}} \tag{2.20}$$

$$\alpha_{new} = \frac{\alpha}{(k-1)}, \tag{2.21}$$

where p_α values are based on standardized range statistics divided by $\sqrt{2}$, c is the total number of data sets in comparison, and k is the number of algorithms.

The friendly graphical analysis proposed by Demsar (DEMšAR, 2006) permits a rapid identification of ranked classifiers and CD value, in a simple and unique diagram as Fig. 4.

The diagram shows CD value in evidence, drawn over the main bar, where the equivalent classifiers are also aligned. In case of Bonferroni-Dunn is the established test,

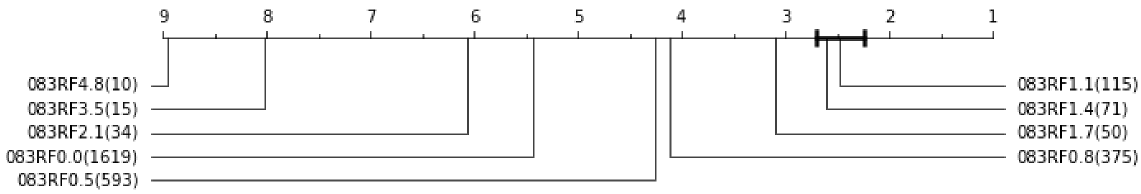

Figure 4 – CD diagram example : comparison between RF models. The higher the position on average ranking, the better the model. The black line over the bar emphasizes those models which rank are significantly equivalent, according to CD value.

the CD value is calculated in reference to only one control classifier. It might be defined at SciPy algorithm´s variables as detailed in Appendix A.

2.5 Systematic Mapping

This section is composed of activities performed during the system mapping, the applied techniques and tools used from the definition of the research quests, through the execution of the research itself and the analysis of the inclusion and exclusion criteria, ending in the discussion of the selected articles.

2.5.1 Definition of Research Questions

To detail the objectives and determine the research question, we used the Parsifal tool to store and organize the information established in the mapping protocol. Thus, using the terms suggested by the PICO technique we arrive at the definition of the research question : What are the machine learning techniques applied in the diagnosis of dyscalculia and/or classification of its developmental sub-types from psychometric data?

2.5.2 Extraction and Mapping of Studies

To conduct the research of articles we considered the repositories ACM Digital, IEEE, Pub Med, Science Direct, Scorpus and Springer. In this study, only documents typified as scientific articles, published in English, between the years 2010 and 2021 were considered. We note that book chapters, copyrighted materials and other publications were not accepted in this mapping. In some of the repositories, where the area of studies was considered a search key, articles related to the social sciences, sociology, biology and the like were disregarded. The selected research articles distribution over repositories is in Tab. 2

	String Selection	After Exclusion/ Inclusion Criteria	After Abstract Reading
ACM Library	16	3	0
Science Direct	235	13	1
Scorpus	6	4	0
Springer	80	4	2
IEE	40	11	5
PubMed	2	1	0

Table 2 – Selected research articles distribution over repositories

Next, we move on to the analysis of synonyms for the search keywords and arrive at the following search terms: dyscalculia or specific learning disorder or impaired ability in numerical concepts or mathematical learning deficits and machine learning. The selection process is demonstrated in Fig. 5

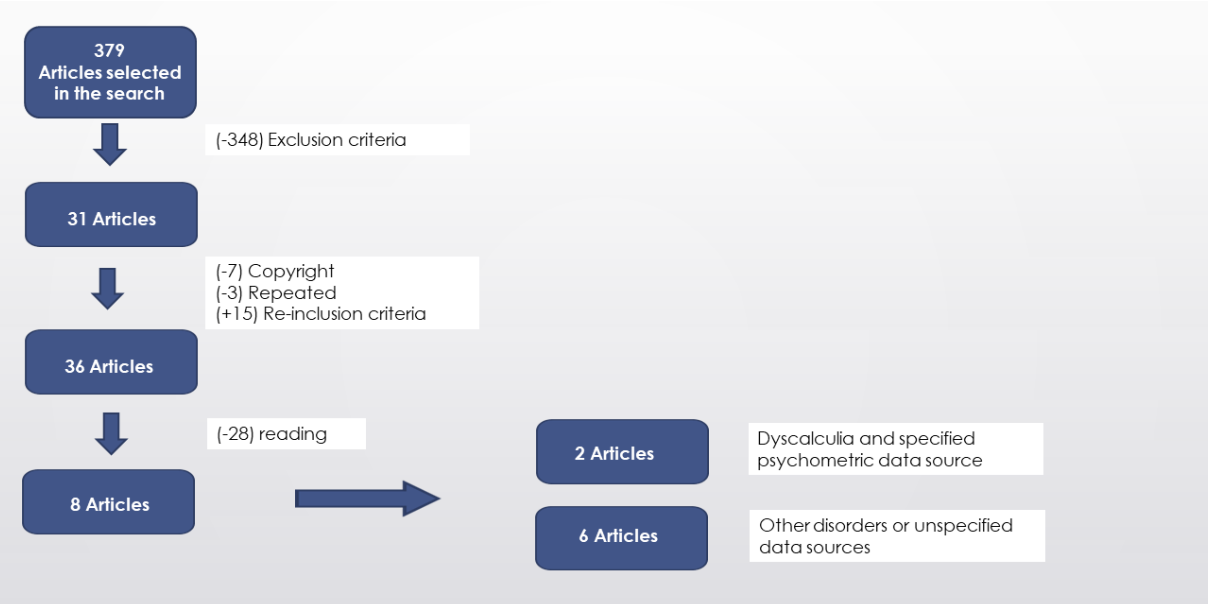

Figure 5 – Articles Selection Flow: The search results identified 379 articles. After applying the exclusion terms, we reduced the selection to 31 articles. Of these, 3 duplicate articles and 7 articles that were not accessible due to copyright were removed. In the inclusion, 15 articles were reconsidered. Thus, for the reading phase of the abstracts, 36 remained selected articles. Among the articles read, 8 met the research question satisfactorily regarding the use of machine learning techniques, although 2 deal specifically with other disorders (autism and dyslexia) and only 2 refer to the application for diagnosis of dyscalculia based on clearly specified psychometric data.

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2016	An extension of the FURIA classification algorithm to low quality data through fuzzy rankings and its application to the early diagnosis of dyslexia - Science Direct	FURIA (PALACIOS et al., 2016).
2019	Pubudu Deep Learning Based Screening And Intervention of Dyslexia Dysgraphia and Dyscalculia - IEEE	CNN (KARIYAWASAM et al., 2019).
2019	Dyscalculia Detection Using Machine Learning - Springer ©	Random Forest (SUBRAMANYAM; JYRWA; BANSINGHANI, 2019).
2020	Detection of Dyscalculia Using Machine Learning - IEEE	Random Forest (GIRI et al., 2020).
2021	Mohan-Paramasivam Article Feature Reduction Using SVM-RFETe - Springer	LibSVM, Naive-Bayes, SVM-RFE, Ibk (MOHAN; PARAMASIVAM, 2021).
2021	A Mobile Based Screening and Refinement System to Identify the Risk of Dyscalculia and Dysgraphia Learning Disabilities in Primary School School Students - IEEE	SVM (HEWAPATHIRANA, 2021).
2021	Early Diagnosing and Identifying Tool for Specific Learning Disability using Decision Tree Algorithm - IEEE	Decision Tree (DEVI et al., 2021).
2021	Identification of Dyscalculia Using Supervised Machine Learning Algorithms - IEEE	SVM, Logistic Regression, Naive Bayes, Random Forest (DHINGRA; GARG; PUJARI, 2021).

Table 3 – Identified techniques in selected articles of systematic mapping, years 2010-2021

on clearly specified psychometric data. The diagnostic studies of dyscalculia based on collection through application or questionnaires carried out in a school environment were considered for analysis, although they did not specifically meet the question of data origin, due to their contribution to the understanding of the possibilities of applying machine learning techniques. The following table identifies answers to our research question by presenting the techniques used in the selected articles.

2.5.3 Discussion

Recently, several machine learning techniques have been used in varied approaches by researchers in the expectation of reducing time and costs for various specific learning disorders diagnosis. The approaches and applied techniques are different in each of the studies, as well as the depth of discussion.

In the study published in 2016 in Spain, authors Palacios and others compare the efficiency of the FURIA (Fuzzy Unordered Rules Induction Algorithm) algorithm with the use of training data of low and high technical quality for the diagnosis of dyslexia, against the application of other algorithms such as BOOSTING (PALACIOS et al., 2016).

In 2019, Kariyawasam and others released a study based on data collected by a web application for the diagnosis of learning difficulties, including dyscalculia. To make up the data set, mathematical skill tests were applied and based on the execution time and the score achieved, a classifier using the CNN technique was built (KARIYAWASAM et al., 2019).

In 2019-2020, two articles were published by the researcher team of B.Y.L. Nair Ch. Hospital in Mumbai, India. Subramanyam (2019) and Giri (2020) and other researchers used 650 samples of the WJT (Test IV) for cognitive skills, specifically those related to mathematical skills, namely Test 5 (Math and Calculations), Test 6 (Math Fluency), Test 10 (Applied Problems), Quantitative Concepts (18A) and Test 18B (Number Series). The selected features, joined to age and IQ score for each patient, compose the protocol adopted for the diagnosis of dyscalculia in the department of psychiatry of the hospital. The model was constructed using all variables of the training data set and the Gini index criterion. All variables coming from the WJT were transformed to -1/0/1 for incorrect, unanswered, and correct questions, respectively. The Random Forest algorithm was used to classify and obtain the analysis of importance of the variables, and results of high performance were reported (SUBRAMANYAM; JYRWA; BANSINGHANI, 2019; GIRI et al., 2020).

In 2020, by Mohan and others, the study regarding the diagnosis of autism spectrum syndrome was published making a comparison between the application of the LibSVM, IBk and Naive Bayes techniques, after dimensional reduction with SVM-RFE, which assigned weighting to the variables and classifies them, improving the diagnostic capacity of the models generated by all applied machine learning techniques (MOHAN; PARAMASIVAM, 2021).

Hewapathirana of Sri Lanka published her study in 2021, where she uses the 'Nana Shilpa' app to perform data collection and identify children with characteristics of various learning disabilities. For each identified difficulty, specific machine learning techniques are used, listed by the author. In the case of dyscalculia, the supervised Support Vector

Machine (SVM) technique was adopted, which applied to selected parameters differentiates students into two classes. The proposed model of predicting the risk of dyscalculia requires that students identified with mathematical difficulties later be evaluated by a professional in the area to confirm the diagnosis(HEWAPATHIRANA, 2021).

In 2021, Devi and other researchers published tests conducted with 40 students, using a web application for diagnosis of dyscalculia, among other difficulties, containing questions elaborated based on the Woodcock-Johnson Test (WJT). In that study, the machine learning technique was Decision Tree Algorithm (DEVI et al., 2021).

In addition, in 2021 Dhingra and other researchers performed a comparison among four supervised machine learning techniques (Support Vector Machine, Logistic Regression, Naive Bayes and Random Forest) for key model performance metrics. Data from 100 children aged 6-7 years were collected for the study. All the variables presented as study parameters were binary, for all applied techniques (DHINGRA; GARG; PUJARI, 2021).

We have found some common limits among the above-mentioned works, such as the binary classification approach, exclusive psychometric data source and reduced number of variables for learning disorder simultaneously analysis. It is worth mentioning that most articles led to good performance rates models, whenever considering mostly the categorical data. We observe an opportunity for studies whose approach is carried out with multiclass machine learning methods, where the comorbidity influence and diagnose heterogeneity (HAASE et al., 2012; HABERSTROH; SCHULTE-KORNE, 2019) can be characterized. Also, psychometric cut-offs are recognized to be a support diagnosis instrument that requires joint clinical evaluation, (MAMMARELLA et al., 2021; WEISS, 2020; GOMIDES et al., 2021) what were not clearly approached on available studies. Moreover, when applying a diagnosis specialized protocol, one expects the dimensionality to increase, and data accommodates numerical and categorical results.

3

Methodology

3.1 Problem Definition

We assume $(x_i \in D)$, $(D = R^N)$ a patient or example, with N dimensions, where $(X = (x_{i_1}, \ldots x_{i_n})$ is a vector of discrete variables , n is the size of the variable vector, and $i = 1, 2...m$, m is the number of examples. The element x_i is associated with a unique class y_i, $Y = (y_1, ...y_q)$ where q is the number of classes and Y is the set of possible classes of diagnosis.

3.2 Data Structure Analysis & Definition

The target of this step is to recognize the composition of the data, its format, and its origin in order to establish the project's data dictionary. The main features analyzed on data sets during this dissertation follows:

- Sample size: very large data sets can compromise execution, while the opposite can bias the sample, impairing the quality of the prediction model.
- Dimensionality: data sets with large dimensionality often carry a lot of redundancy and irrelevant attributes that compromise the performance of machine learning methods. There is also an impact on storage capacity and demand for processing time. This characteristic also reflects in the determination of the rule of division of the nodes and in the choice of use of dimensionality reduction techniques.
- Data structure complexity: whether composed of multiple continuous and categorical or Boolean data types. The need for scaling, normalization, and transformation of data during pre-processing depends on the conditions of raw data.

- Missing values: the existence of high-level missing data can compromise the quality of the classifiers. Some techniques for filling in the data will be evaluated in this theme.

- Data behavior analysis: analyze issues like correlation, general trends, outliers and statistics through visualization, plots and available documentation.

The original data set consists of 4057 records and 4626 variables, with data recorded between the years 2011 and 2018, containing the entire history of ambulatory attendance organized in several projects. The use and access of information comply and are duly authorized by the National Health Council - Ethics in Research (CONEP).

Beginning with raw data set, after exploring some possible approaches, addressing data quality issues and based on existing documentation, we find the data set is composed by specific tests results and value-added as variables(PAIVA, 2021). Thus, each result of the tests carried out, in all phases of the evaluation, is considered as a specific variable of the project data set. In addition to the variables that represent specific test results, the data set also includes calculated values (variables of added value), namely, the sum of the test scores, according to specific application standards, and the calculation of the standard score (or z-score), which corresponds to the number of standard deviations above or below the population mean. The complete dataset subdivision schema can be seen in Fig.6.

To obtain the final version of data set, several filters were applied to original data set, following specialist's orientation, in order to keep relevant examples of outpatient protocol NUMERO and the project *Ambulatorio*. The pseudo-algorithm deployed on this activity is detailed in Appendix D. To obtain the data set for this study, the following filters were applied to:

- Removal of patient identification data: name, address, school name, among others that enable patient identification;

- Selection of records of the *Ambulatorio* project: among the projects of the LND-UFMG, those named as Outpatient Clinic refer to the scope of this study;

- Processing of data identified as null but filled with other values assumed by laboratory technicians (named as rule 333);

- Deletion of complete columns with null variables: the original database contains fields not used in laboratory activities:

- Deletion of columns identified as indifferent: according to the analysis of the laboratory team, columns of meaningless values were listed, although filled;

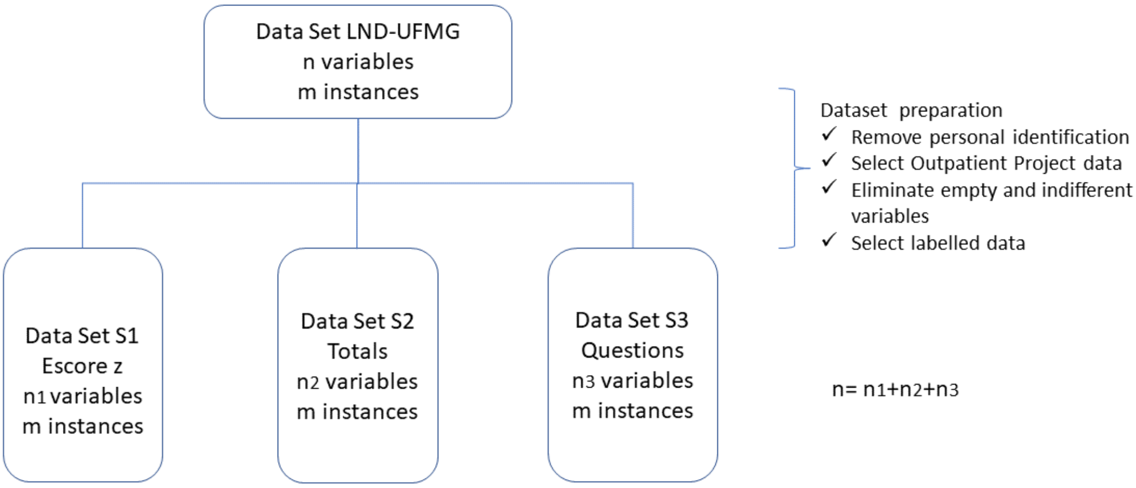


Figure 6 – According to discussions with the LND-UFMG team :subset S1 is composed by calculated value, the standard score (or z-score), which corresponds to the number of standard deviations above or below the population mean, subset S2 contains calculated values (variables of added value), namely, the sum of the test scores, according to specific instruments standards and subset S3 is composed by result of each instrument's test carried out, in all phases of the evaluation process. While subsets S1 and S2 are formed only by continuous data, S3 is composed of categorical and continuous data.

- Selection of patients who completed the ENC phase, with results recorded in column GRUPO_DIAG_TA.

Complementary, the patient´s path throughout diagnostic process determines the hierarchical characteristic of the resulting data sets. Starting in the ENI phase, the patients whose psychometric results and clinical evaluation indicated compliance with the criteria of the diagnostic hypothesis, followed the process for the ENC phase. During the diagnosis process flow, four steps emerged, concerning groups of diagnosis. We considered these four steps as cut points to build data sets, each one with its own diagnosis classes, so we were able to compare the protocol characteristics along whole process flow (Fig. 7).

Finally, to every classification analysis we considered solely subset S3, within the bounds of all 4 versions of dataset, according cut points on Fig. 7. Being so, we prevent no classification tag and no value-added information within raw data. From now on, when we mention the data set variables, the referable subset is S3, and data set names are defined as dataset083, dataset149, dataset364 and dataset762.

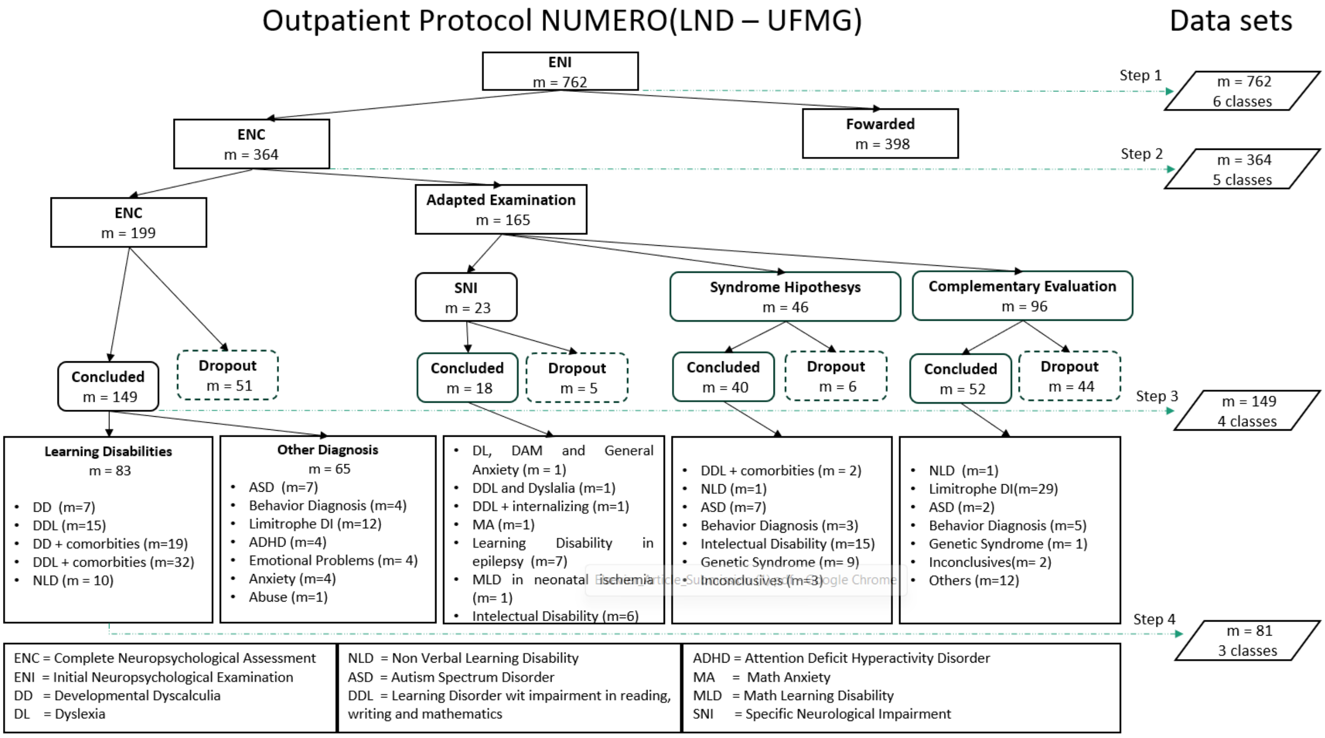


Figure 7 – Diagnosis process flow and data sets, based on PAIVA, 2021 (PAIVA, 2021). Four stages in the process flow might be considered for analysis. Steps 1 and 2 in figure, are related to data sets from ENI phase´s instruments only and steps3 and 4 are built merging ENI and ENC phases´ instruments. As further we go into process flow, the missing values and the number of diagnosis classes decreases, and it becomes more specialized. The initial classes are groups of characteristics, while at last step we have more specific diagnosis.

3.3 Proposed Framework

In this section we discuss every particular characteristic of the proposed framework. Using the open source packages Scikit -Learn (AL., 2011), missingpy (A.BHATTARAI, 2018), SciPy (MAYOROV, 2020) and Orange Datamining (CURK et al., 2013) experiments were conducted involving data preprocessing, feature selection, Random Forests classification, multiclass ROC Curve metrics, statistics tests and variable ranking analysis. All source packages and tools applied during this dissertation are described in details in Appendix A.

The proposal framework aims to identify a selection of variables which produces the best classification model, in terms of performance and explore their importance for each diagnosis class of MLD. Since we may have uncountable combinations of those variables, we initially group them according to variance through HCA method, and test obtained models comparing the respective AUC metrics, using statistics tests. Every time a winner group appears, the algorithm breaks down the selection and test it again, until the established criteria is achieved. The number of executions demanded may vary according to the initial settings, and thus the precision of chosen variable selection. Those initial settings will be examined in the next section. It is worth recording that before we arrived to following framework combining HCA, multiclass RF, Friedman and Bonferroni-Dunn test, simulations were made comparing two different multiclass RF approaches and SVM classifier, where preprocessing method was KNN and statistics tests applied were based on Friedman/Wilcoxon and Nemenyi tests. This intermediate work led us to some important conclusions, and we discuss those in Intermediate Results section in Appendix D.

3.3.1 Overview

The proposed framework, as illustrated in Fig. 8, comprises eight steps, which are described in detail below:

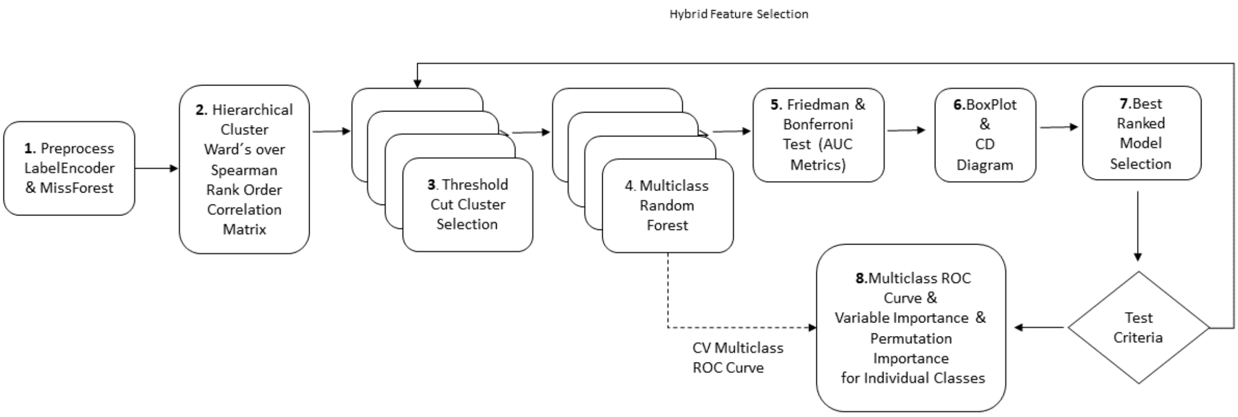


Figure 8 – Proposed Framework Flow: Starting with a preprocessed data set (1) without missing value, we obtain a HCA with *scypi.cluster.hierarchy* over a *scipy.spearman* correlation matrix, converted to a distance matrix (2). Then, we choose some height threshold cuts t (3), fit respective leading variables to $sklearn.multiclass.OneVsRestClassifier$ RF, score each one with $sklearnmetrics = roc\_auc\_score$, $average = macro$, $multiclass = ovr$ based on a $sklearn.modelselection.RepeatedStratifiedKFold$ (4). The AUC values are submitted to Friedman/Wilcoxon (5) and a CD diagram based on Bonferroni-Dunn is generated (6). The best ranked model is set as control for Bonferroni comparisons (7). When the established criteria is achieved, the process stops and the chosen t multiclass ROC is plotted and the variable ranking for each class is presented (8).

Based on Random Forest technique, we propose a multiclass framework, that considers an overlap diagnose of DD and comorbidity, according to NUMERO Outpatient Protocol, a specialized protocol for developmental dyscalculia and comorbidity diagnosis. An additional noteworthy aspect of our approach is the consideration of uper level of missing values in the data set. For dimensionality reduction, we combine a hierarchical cluster threshold selection with RF performance metrics criteria, based on ROC curve analysis.

Finally, our proposed framework integrates various RF-based tools in conjunction with statistical tests such as Friedman, Wilcoxon, and Bonferroni-Dunn. By combining these techniques, we establish a reliable approach for developing a multiclass classifier based on psychometric protocols. This comprehensive framework ensures the performance and validity of the classifier, providing a robust solution for diagnosing learning disorders across multiple classes.

3.3.2 General Characteristics and Parameters

The main goal of this step is to recognize the parameters and characteristics that involved premises and influenced decisions taking during this project among data sets characteristics, RF algorithm and framework parameters:

- Small sample size: Due to the simplicity and the explainable ability of Random Forest (RF), good performance and ability to adapt to data sets with small number of samples with high dimensionality and high complexity (SCORNET; BIAU; VERT, 2015), our approach is able to attend to the data set features. When selecting specific variables for node split, RF increases a layer of randomness to bagging, and permits each tree of the forest to be built using a different bootstrap sample of the data. The good performance of RF is related to the strength of each tree, together with the small correlation among the trees of the forest. Those features provide capability for RF to efficiently deal with high dimensional multivariate data (number of variables greatly exceed the number of examples), reduced sample size and mixed data types (BREIMAN, 1996; BREIMAN, 2001; BREIMAN, 2004; GENUER, 2012).

- High dimensionality: Data sets with large dimensionality often carry a lot of redundancy and irrelevant attributes that compromise the performance of machine learning methods. There is also an impact on storage capacity and demand for processing time. This characteristic also reflects in the determination of the rule of division of the nodes and in the choice of use of dimensionality reduction techniques, whenever applicable;

- Data structure complexity: whether composed of multiple numerical and categorical or Boolean data types. The need for transformation of data revealed during preprocessing due the conditions of the original data. Moreover we assumed some premises for categorical data in order to accomplish our dimensional reduction strategy. This issue is better discussed on next section.

- Missing values: Due to elevated missing values in data sets and to attend a scikit-learn requirement, the imputation is executed before splitting dataset into training and test set.

- RF parameters : We applied One-Over-Rest Random Forest (RF) method for binary classification. At a certain point we evaluated using the Multi-object Decision Tree (MODT), in which multiple classification is performed in a way unique. But being the predictive performance of both rating models Single Objective Decision Tree and Multi-Objective Decision Tree very similar (KOCEV et al., 2007), we opted for the execution in the simplified mode initially, in the expectation of better interpret ability for results. Following the as simple as possible approach method, we stand for using sklearn models on suggested RF parameter.

  - Class sklearn.ensemble.RandomForestClassifier :

    * n_estimators=100 : number of trees in forest
    * criterion='gini' : chosen method for impurity calculation
    * max_depth=None : no pruning method applied
    * min_samples_split=2 : minimum sample number to split a node
    * min_samples_leaf=1 : minimum sample number to be at leaf
    * min_weight_fraction_leaf=0.0 : no weight concept were used
    * max_features= sqrt : method to obtain the number of variables when bootstrap is True
    * max_leaf_nodes=None : no limit is applied
    * min_impurity_decrease=0.0 : no impurity decrease control
    * bootstrap=True : if bootstrap sample is used to build trees
    * oob_score=False : not used
    * ccp_alpha=0.0 : no cost complexity pruning
    * random_state=None
    * class_weight=None : no weight was applied
    * max_samples=None :no control on sample size established

- Framework parameters : there are three main parameters outside machine learning methods that might be observed in order to understand the framework results, as follows:

- Delta: variation at t (threshold cut), comparing last and current laps, to define stopping criteria. If the variation is within delta value, the algorithm stops.
- Initial T: vector of t values to be considered. It worth make multiple analysis on HCA results and framework simulations to guarantee the best performance on this parameter. The farther from ideal result it is set at the beginning, the longer it is expected to be the running time.
- Trials x splits: these are the respective number of repetition and number of cross-validation splits, which determines the normal distribution for AUC values. We assume the minimum value for our tests as trials = 100 and splits = 10. Rising in trial numbers were considered during tests with no addition in quality results while the computing time increases significantly.

3.3.3 Preprocessing

The step 1 (Fig. 8) aims to reduce processing demand and avoid testing highly correlated variables that have little to add to the model in terms of its predictive capacity, through the selection and preparation of the data set. Here we prepare the data sets by filtering the data selected for the study, removing redundant and invalid or inconsistent values and joining data.

In this dissertation, categorical variables are numerically coded. The categorical variables can be binary or multiple, in each specific case, the number of possible categories to be assumed by a given categorical variable was included in a vector of integers.

Due to the high cardinality of categorical variables, to calculate Spearman rank correlation on variable selection step, and assuming an existing ordinal relation within categorical data, we have chosen to apply Sklearn preprocessing LabelEncoderd, which is detailed in Appendix A.

An additional noteworthy aspect of our approach is the consideration of missing values in the data set. To tackle this issue, we utilized the MissForest algorithm, a Random Forest (RF) based imputation technique. This supervised imputation mechanism is capable of effectively handling both categorical and continuous variables simultaneously, without the need for specific parameters or prior knowledge regarding data distribution (STEKHOVEN; BUHLMANN, 2012). By incorporating MissForest into our methodology, we ensure robust imputation of missing values in the data set. MissForest algorithm is detailed on Appendix A.

Furthermore on Appendix D we discuss some intermediate results where we initially approach the missing values treatment with KNN technique, considering that only numerical variables presented missing values.

3.3.4 Hybrid Feature Selection

In this section we describe Framework Flow Steps (2-7)(Fig. 9), the hybrid feature selection, implemented for selecting the variables by combining filter and wrapper method. Feature selection intends to improve the stability, reduce the dimensionality of variables, and remove irrelevant features. Over the subset obtained after filtering, we apply a RF multiclass classification algorithm as a complementary wrapper method.

Primarily, we approach multicollinearity by performing HCA (step 2) on the features' Spearman rank-order correlation matrix (AL., 2011). Spearman rank correlation is non-parametric and does not require normal distribution of data (CURK et al., 2013). We obtain Spearman correlation matrix for all variables and a cluster hierarchy linkage is performed, with Ward method option, over the correlation matrix, forming clusters that minimizes the total within-cluster variance.
To compute the distance d between two clusters s and p, Ward method uses the Ward variance minimization algorithm. The distance $d(u, v)$ is computed as follows (MüLLNER, 2011) :

$$d(u,v) = \sqrt{\frac{|v|+|s|}{C}d(v,s)^2 + \frac{|v|+|p|}{C}d(v,p)^2 - \frac{|v|}{C}d(s,p)^2} \tag{3.1}$$

Variable u is the newly joined cluster consisting of clusters s and p, v is an unused cluster in the forest,

$$C = |v| + |s| + |p| \tag{3.2}$$

From the HCA (step 3), several flat clusters are obtained from distance threshold (t) selected values (Fig. 9) and stored in a T vector, $T = (t_1, t_2...t_c)$, c is the number of total clusters from a linear and equidistant values selection. For each distance threshold t, we keep a single feature (leader) from every cluster formed at that distance to compose the new subset. We start with an initial guess, $|T| = 9$ for practical reasons. Details on SciPy hierarchical cluster implemented here appears in Appendix A.

At every round executed (step 4), for each subset, a One-Vs-Rest Random Forest (OVR-RF) classifier is fitted. In addition to its computational efficiency, one advantage of this approach is its interpret-ability and possibly gaining in knowledge about each class. This is a commonly used strategy for multiclass classification and is a fair default choice.

To assess performance for each specific RF model, the algorithm is executed 100 repetitions of 10-fold cross-validation, considering multiclass stratification. To compare the performance between RF models, we calculate the macro averaged area-under-curve (AUC)

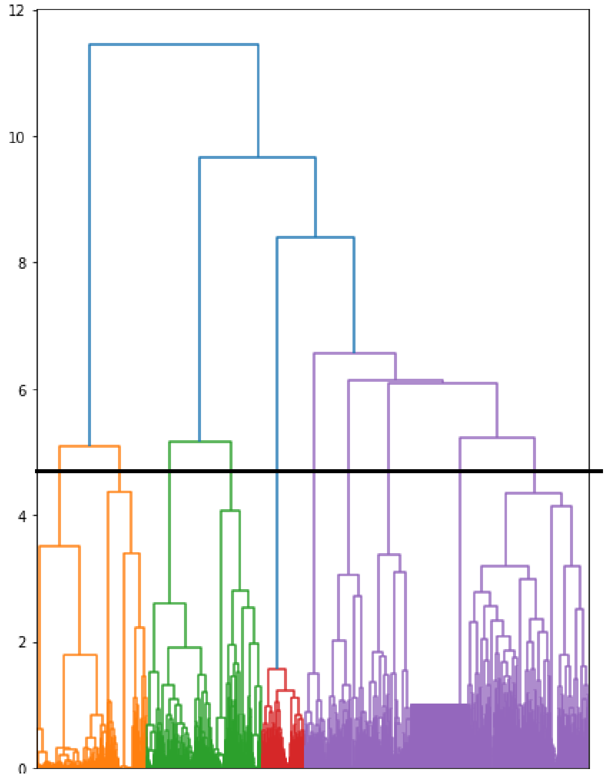


Figure 9 – Hierarchical Cluster Algorithm: To retrieve flat partitions from a dendrogram, we choose the height for cutting. At a given t distance threshold, we obtain a flat clustering that is a partition of the full data set, the selected cluster leading variables. For HCA we use *scypi.cluster.hierarchy* over a *scipy.spearman* correlation matrix.

over a balanced stratified split at 50/50 ratio and repeating the process after swapping the train and test sets. Thus, combined to sklearn.CVRepeatedKfold, this ratio split guarantees that no unique example participates in training and test, while avoiding any variance at results based on split random state. We also balance both test and train set separately, applying *imblearn.over_sampling.randomOverSampler* technique. The one-vs-rest strategy, also known as one-vs-all, is implemented in sklearn.multiclass.OneVsRestClassifier where each class is fitted against all the other classes (Appendix A).

Based on AUC metrics table (step 5), to investigate if RF models are significantly different, initially we apply Wilcoxon test when $|T| = 2$ or Friedman test when $|T| > 2$, considering a significance level of 5%. Whether Friedman (or Wilcoxon) test rejects the null hypothesis - which states that all RF models are equivalent, and their ranks should be equal - or not, the post-hoc Bonferroni-Dunn test is applied. We execute Bonferroni test to reduce family-wise error rate (FWER). When p-value α is divided by the number of comparisons being made $(k-1)$, to obtain a conservative value of significance α_{new}(8)(DEMšAR, 2006). In any case of Friedman/Wilcoxon response, the model's final evaluation is based on best ranked model in CD diagram. For all T length, $|T| > 1$, an average ranking and an associated critical distance (CD) is calculated to build the CD diagram. To execute Bonferroni and generate CD diagram, we use the best average ranked model as the control to comparisons.

In the sequential execution (step 6) examining CD diagram, the best ranked RF model and respective cluster distance threshold t can be chosen for another round. We repeat this procedure until the selection criteria is achieved (step 7). Therefore, for each lap repeatedly, we calculate the difference between the last lap chosen value t and the new one, until it converges within an acceptable difference value δ.

Unlikely Demsar (2006), we here run the RF classifiers with identical parameters and compare them as different classifiers models. We consider it due to RF´s multiple level randomization, ensemble nature and consistency (SCORNET; BIAU; VERT, 2015; GENUER, 2012). Therefore, for this dissertation, in equation (1.11) , k is actually the possible number of different models obtained from an unique RF algorithm, with none random state parameter, varying with subset selection (t) and c is equivalent to total number of distance threshold cuts compared or number of subsets.

After achieving the stopping criteria (step 8), starting with a binary label vector y, based on classes from selected model, a multiclass ROC curve (one over rest model) and a variable ranking, based on RF variable importance (Gini importance) and permutation importance methods, are generated for each diagnosis class.

We use both permutation importance and Gini importance tools as ranking method attending to Gini´s influence toWards high cardinality variables while permutation importance does not suffer from this kind of influence(NEMBRINI; KöNIG; WRIGHT, 2018; STROBL et al., 2007; STROBL et al., 2008). In order to allow a comparison or even an average rank construction we consider both importance analysis methods.

While RF Gini importance demonstrates the variable importance during estimator building, the higher the permutation importance of a variable, the more relevant the variable is for the overall performance of the prediction.

At every round executed, for each subset, an One-Over-Rest Random Forest (OVR-RF) classifier is fitted. The one-vs-rest strategy, also known as one-vs-all, is implemented in $sklearn.multiclass.OneVsRestClassifier$ where each class is fitted against all the other classes.

4

Results and Discussion

In this chapter we present and discuss the framework performance after application on every data set level of UFMG protocol (Fig.7).

4.1 Complexity Analysis

Table 4 shows initial numbers and missing values percentage related to each process step.

Table 4 – Data set Initial Numbers of raw data sets. |D| is the number of examples, |X| is the variable numerosity, |Y| is the number of possible classes and %MISS refers to missing values percentages.

Data set name	$\|D\|$	$\|X\|$	$\|Y\|$	***% MISS***
Dataset762	762	1568	6	71
Dataset364	364	1572	5	65
Dataset149	150	1569	4	58
Dataset083	81	1560	3	53

As it may be observed in Tab. 4, when generating the dataset versions, some selection criteria as e.g, delete full nan columns, can return a different number of valid columns (variables). The withdrawal of patients and changes in diagnosis instruments during the data collection period are the main causes of high missing values presented.

4.2 Data set Preparation

The data set input for this stage has already determined version, as beforehand mentioned Dataset083, Dataset149, Dataset364 and Dataset762. It is worth noticing that, whether this selection version step is postponed, different results could be achieved. The initial size of data sets, including classification column, is in Tab.4.

Before we start the framework analysis, we balance data using *imblearn .over_sampling*. Regarding small sample sizes in use, we understand the oversample method is adequate, where samples of minority classes are randomly repeated to achieve the class balance. Next task is to calculate complexity indicators (section 1.4.2) as demonstrated on Tab.5.

Table 5 – Data Set Complexity Analyses

Name	$\|D\|$	$\|X\|$	$\|Y\|$	***% MISS***	***CPLX***	***D1***	***D2***	***D3***
Dataset762	762	1568	6	71	7E+06	0.90	0.66	0.64
Dataset364	364	1572	5	65	3E+06	0.80	0.58	0.56
Dataset149	150	1569	4	58	9E+05	0.68	0.49	0.46
Dataset083	81	1560	3	53	4E+05	0.60	0.45	0.41

In this step we also prepare 50/50 test train split. Since it is mandatory both test and train to have same length, we have stated here a workaround for unpaired test and train, where minor dataset is completed with one more example copy, although it should turn it back to some imbalance rate. Additionally, in order to keep simple to manage, the class column is kept as last one.

4.3 Framework Application over dataset versions

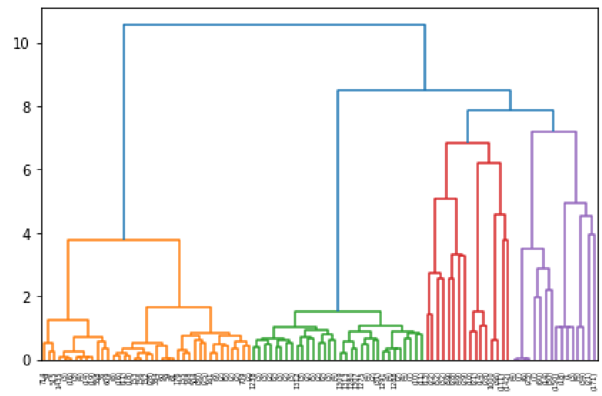
From this section we refer to results of framework application to each specified data set version. After cluster analysis (Fig. 9) and some simulations, we reach an acceptable cluster cut vector as initial guess, covering most significant distance thresholds combination.

Starting from $t = 0.0$ where there is no threshold selection, until $t = 4.8$ distance where only ten clusters were left, in a lean space vector of nine equally distributed values, the distance threshold cuts vector T is determined.

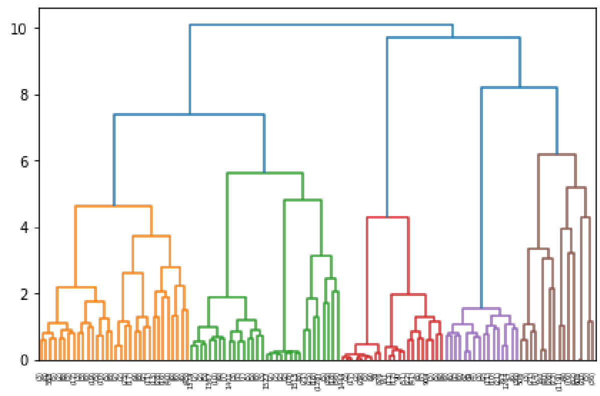
For each distance threshold value in cluster cut vector T, a variable selection, which composes the X vector, and an OVR-RF multiclass classifier is fitted. Then, macro averaged AUC metrics are calculated, and the results are shown on boxplot graph (Fig. 4). To conclude iterative process, it takes as many laps as necessary, beginning with $T = [0.00, 0.50, 0.80, 1.10, 1.40, 1.70, 2.10, 3.50, 4.80]$, in order to attend δ parameter, set to 0.03, while trials is 100 and splits is 10. These parameters are common to every execution of the framework in this dissertation.

4.3.1 Notable points between framework executions

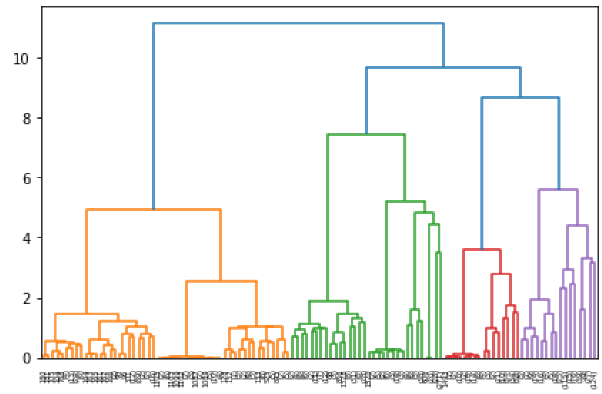
In following figure we may observe some differences in the formed HCA for each data set. It was expected since some divergent characteristics are shown in Tab.4 and Tab.5. The initial T vector is determined considering those HCA differences, and after some simulations.



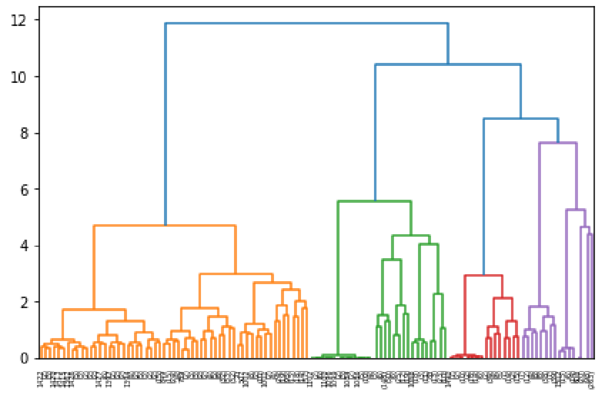
(a) HCA Dataset083



(b) HCA Dataset149



(c) HCA Dataset364



(d) HCA Dataset762

Valid for all framework execution, the box plots produced show increasing similarity as the T vector contains nearer points of threshold cut. Also, outliers percentage remains homogeneous.

Despite all similarity on performance results and outlier percentage, the framework demonstrated capacity to display on CD graphs, the threshold cut selection that provides the best classifier.

It is worthy to mention that all Friedman tests resulted zero, meaning the rejection of null-hypotheses.

Table 6 summarizes the results of all data set framework application. The number of laps in Tab.6 varies according δ (the bigger, the faster to achieve result) and depending how far the initial T is from the best t. Dataset149 happened to be longer running to establish the final result.

Table 6 – Framework Execution Comparison. This table shows for each selected t, the responsive number of variables, laps taken to achieve final result, attending δ and initial T parameters, macro average AUC of best RF classifier and mean outliers in boxplot graphic.

Name	t	$\|D\|$	$\|X\|$	$\|Y\|$	***Laps***	***Macro Average***	***Outliers Mean***
Dataset762	1.6	762	44	6	5	82%	0.7%
Dataset364	1.4	364	64	5	2	76%	0.5%
Dataset149	0.5	150	501	4	2	72%	0.2%
Dataset083	2.33	81	27	3	3	69%	0.4%

Since the chosen model is significantly capable of classify with a macro averaged performance from 69% to 82%, the following discussion is the individual variable impact over each class classifier. The variable list of cluster composition can be found in appendice section A.1 of this dissertation.

Therefore, for all data sets the variable importance plots present always two ranking plots. The left one is a RF gini importance rank and the right one is a permutation importance rank. The same leader variables have different rank positioning depending on the importance calculation. Based on this differences is possible to understand the variable influence on diagnose classification and the effect of each variable numerous options of values in the diagnostic error. Both methods of importance calculation are discussed on the section 1.3.5 of this dissertation.

As products of framework analyses we have box plot and CD graphics, and then, for the best selected t, we have ROC curve and variable importance plots.

In the next section, we present all plots for dataset762, with some explanations, while plots of dataset083, dataset149 and dataset364 are presented in Appendix F.

4.3.2 Dataset 762

The results of framework application over Dataset762 follow in next sections, where we discuss some details during framework execution.

4.3.2.1 Boxplot

In this section we present box plots of framework application over Dataset762. In all box plot graphics, the median's values appears as the box figure and the mean is represented as the red line. Outliers appears as small circles in the normal curve limits of graphic. Outliers tables, i.e. Tabs. 7, 8, 9, 10 and 11 exhibit models' AUC metrics which are out of normal distribution.

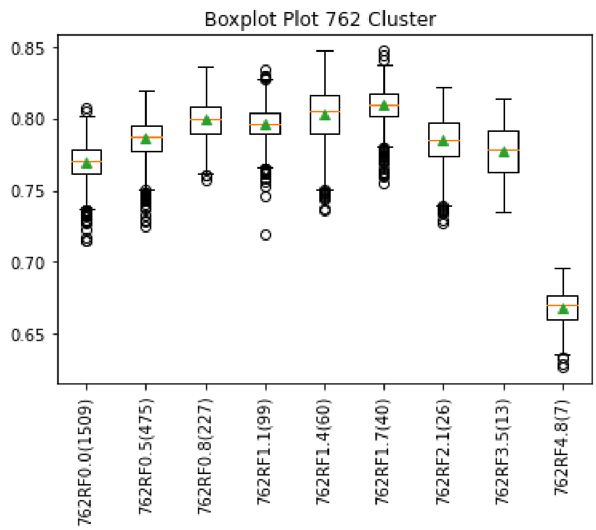


Figure 11 – Box Plot Dataset762 lap01

Threshold (n.variables)	Outliers (by 1000)
762RF0.0(1509)	11
762RF0.5(475)	16
762RF0.8(227)	1
762RF1.1(99)	12
762RF1.4(60)	6
762RF1.7(40)	11
762RF2.1(26)	2
762RF3.5(13)	0
762RF4.8(7)	4

Table 7 – Outliers Dataset762 lap01

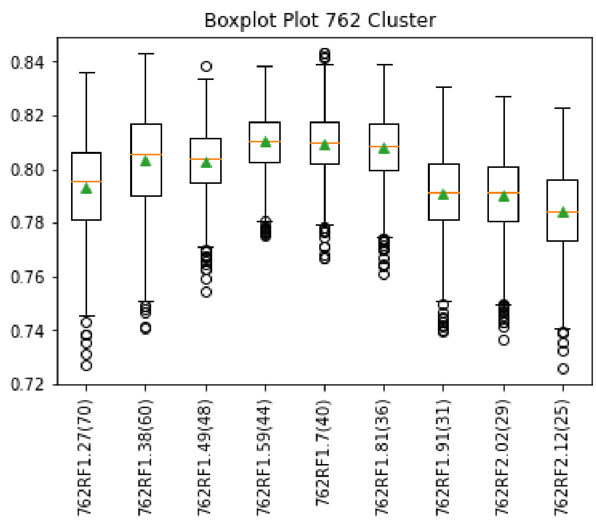


Figure 12 – Box Plot Dataset762 lap02

Threshold (n.variables)	Outliers (by 1000)
762RF1.27(70)	4
762RF1.38(60)	0
762RF1.49(48)	6
762RF1.59(44)	5
762RF1.7(40)	13
762RF1.81(36)	7
762RF1.91(31)	3
762RF2.02(29)	8
762RF2.12(25)	2

Table 8 – Outliers Dataset762 lap02

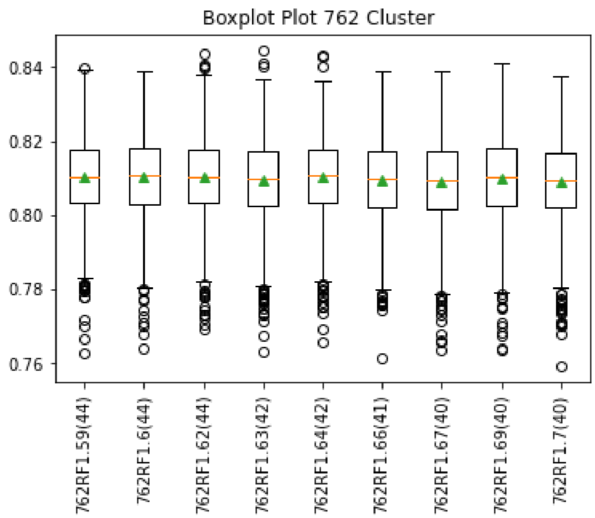


Figure 13 – Box Plot Dataset762 lap03

Threshold (n.variables)	Outliers (by 1000)
762RF1.59(44)	7
762RF1.6(44)	7
762RF1.62(44)	5
762RF1.63(42)	9
762RF1.64(42)	6
762RF1.66(41)	5
762RF1.67(40)	13
762RF1.69(40)	12
762RF1.7(40)	8

Table 9 – Outliers Dataset762 lap03

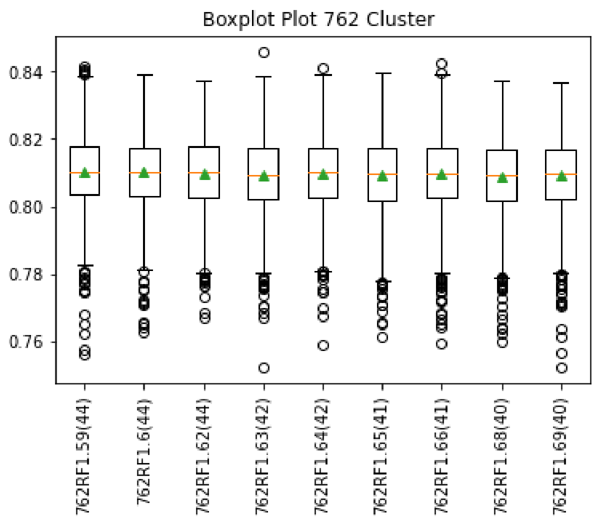


Figure 14 – Box Plot Dataset762 lap04

Threshold (n.variables)	Outliers (by 1000)
762RF1.59(44)	6
762RF1.6(44)	8
762RF1.61(44)	12
762RF1.62(44)	8
762RF1.63(42)	8
762RF1.64(42)	7
762RF1.65(41)	10
762RF1.66(41)	6

Table 10 – Outliers Dataset762 lap04

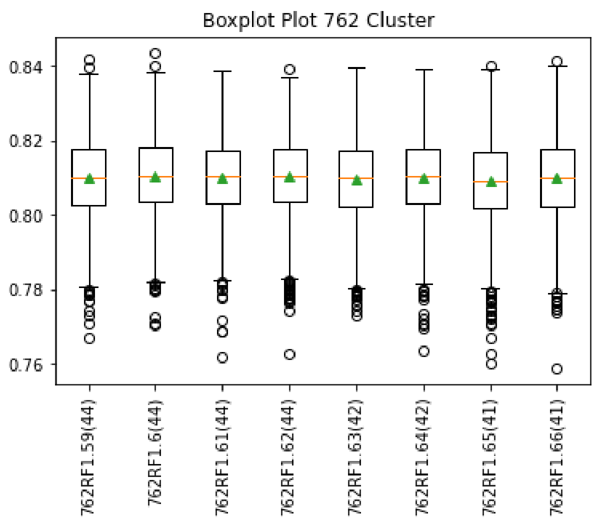


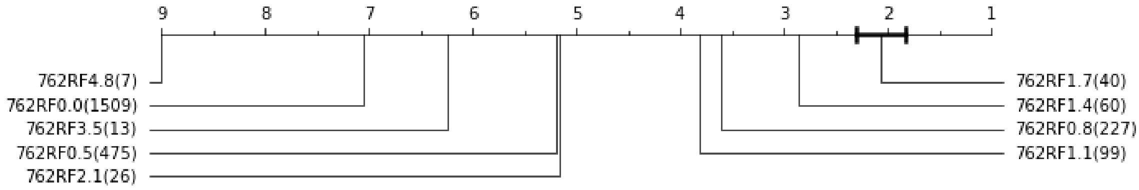
Figure 15 – Box Plot Dataset762 lap05

Threshold (n.variables)	Outliers (by 1000)
762RF1.59(44)	6
762RF1.6(44)	8
762RF1.61(44)	12
762RF1.62(44)	8
762RF1.63(42)	8
762RF1.64(42)	7
762RF1.65(41)	10
762RF1.66(41)	6

Table 11 – Outliers Dataset762 lap05

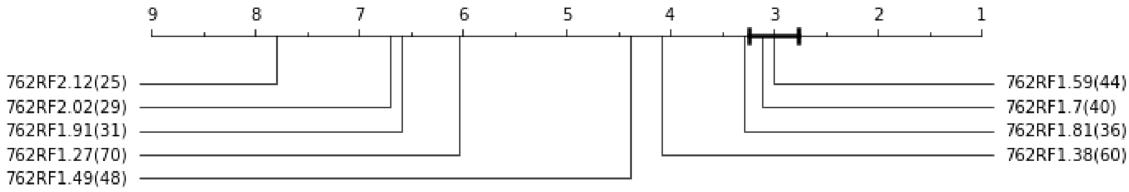
4.3.2.2 CD Graph

In this section we present CD graphs of framework application over Dataset762, where the corresponding t classifiers are compared based on their mean average ranking.

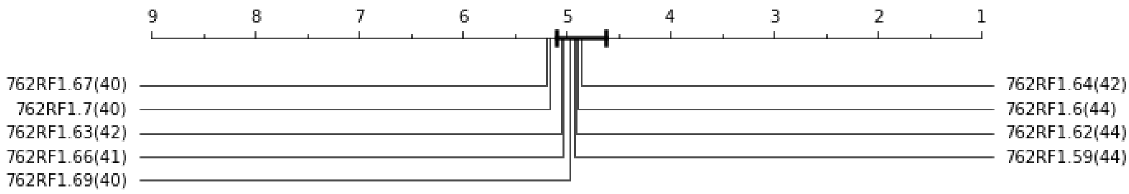


(a) CD graph based on Bonferroni-Dunn. Best average ranked is 762RF1.7, with no equivalence to any other classifier. At this first lap, when no equivalence is achieved between models, but the distance between threshold standard $t = 0.0$ and $t = 1.7$ is bigger than $\delta = 0.03$, another lap is executed considering a new interval around best average ranked threshold, i.e. 75% as inferior limit and 125% as a superior limit

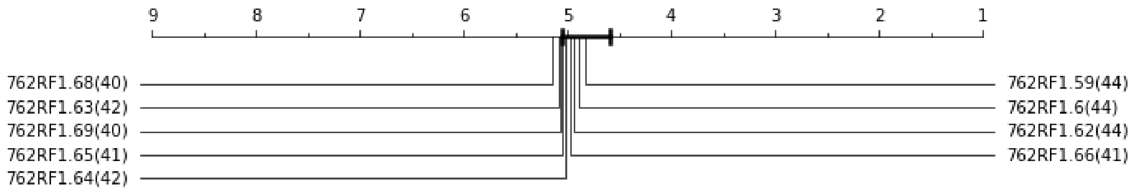
.



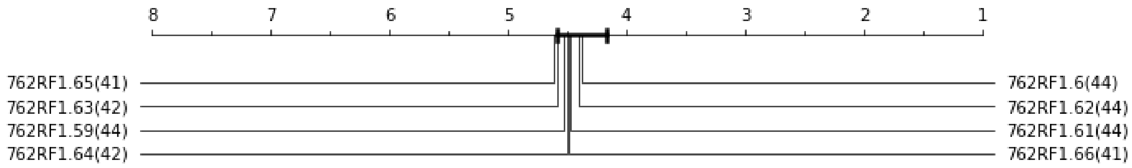
(b) CD graph based on Bonferroni-Dunn. Best average ranked is 762RF1.59, with equivalence to 762RF1.7 classifier. As the distance between last best lap threshold $t = 1.7$ and current $t = 1.59$ is more than $\delta = 0.03$,another lap is executed considering both first and second best average ranked thresholds i.e. $t = 1.59$ and $t = 1.7$.



(c) CD graph based on Bonferroni-Dunn. Best average ranked is 762RF1.64, with equivalence to others classifiers. Yet, despite the equivalence to almost all other models, as the distance between last best threshold $t = 1.59$ and the current $t = 1.64$ is more than $\delta = 0.03$, another lap is executed considering both first and last best average ranked, within the equivalence vector, i.e. $t = 1.59$ and $t = 1.69$.



(a) CD graph based on Bonferroni-Dunn. Best average ranked is 762RF1.59, with equivalence to others classifiers. At this lap, despite the equivalence to other models, as the distance between last best threshold $t = 1.59$ and the current $t = 1.64$ is more than $\delta = 0.03$ yet, again another lap is executed considering both first and last best average ranked, within the equivalence vector, i.e. $t = 1.59$ and $t = 1.66$.



(b) CD graph based on Bonferroni-Dunn. Best average ranked is 083RF1.6, with equivalence to others classifiers. At this lap, despite the equivalence to almost all other models, as the distance between last best threshold $t = 1.59$ and the current $t = 1.60$ is less than $\delta = 0.03$, the process stops and selects $t = 1.60$.

4.3.2.3 ROC Curve

In this section we present the ROC curve of framework application over Dataset762.

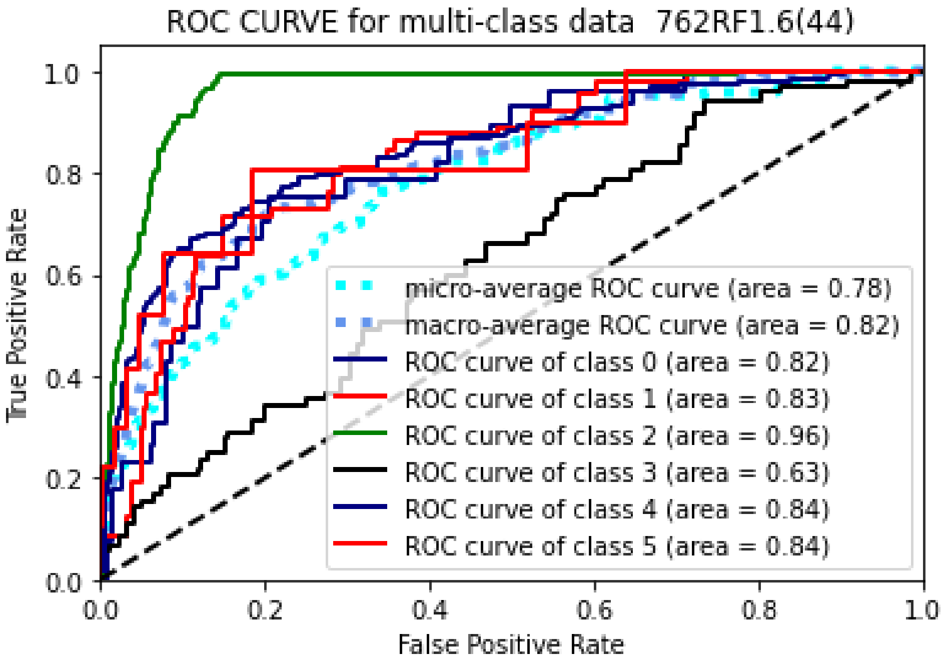


Figure 18 – Multiclass ROC Curve for best ranked RF classifier upon threshold cluster 1.6. With 44 leader variables, the model can perform the classification for diagnosis classes 0, 1 and 2. Performance for each class is shown at one-vs-rest curves.

4.3.2.4 Variable Importance Analyses

In this section we present the variable importance plots of framework application over Dataset762. Based on following variable importance plots, the specialist is able to compare the importance of variables across all classes, referring to diagnose capacity's and the possible error spread, when misplaced values occurs in the psychometric data, for instance.

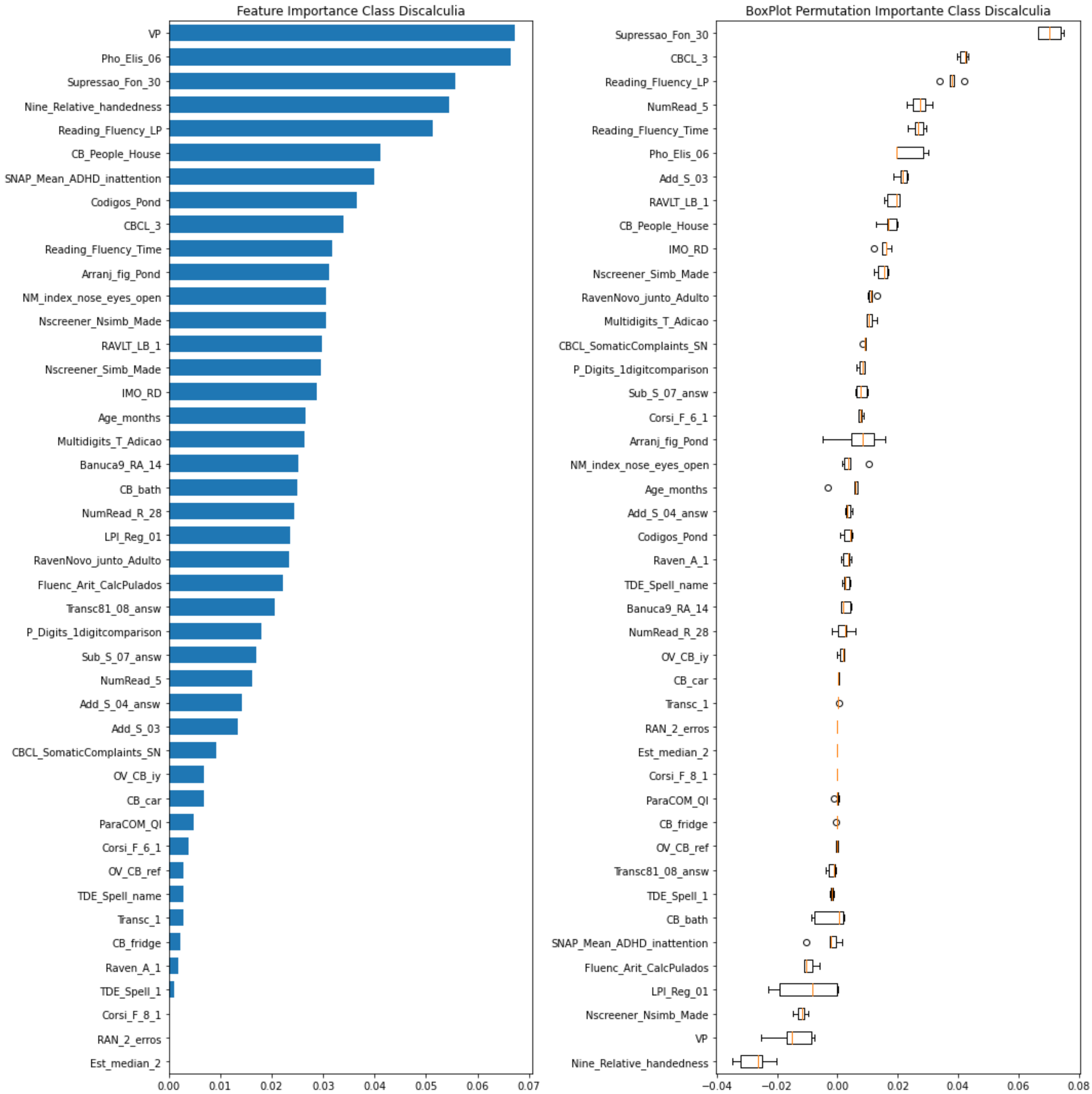


Figure 19 – Dataset762 : Variable Importance of Class Dyscalculia

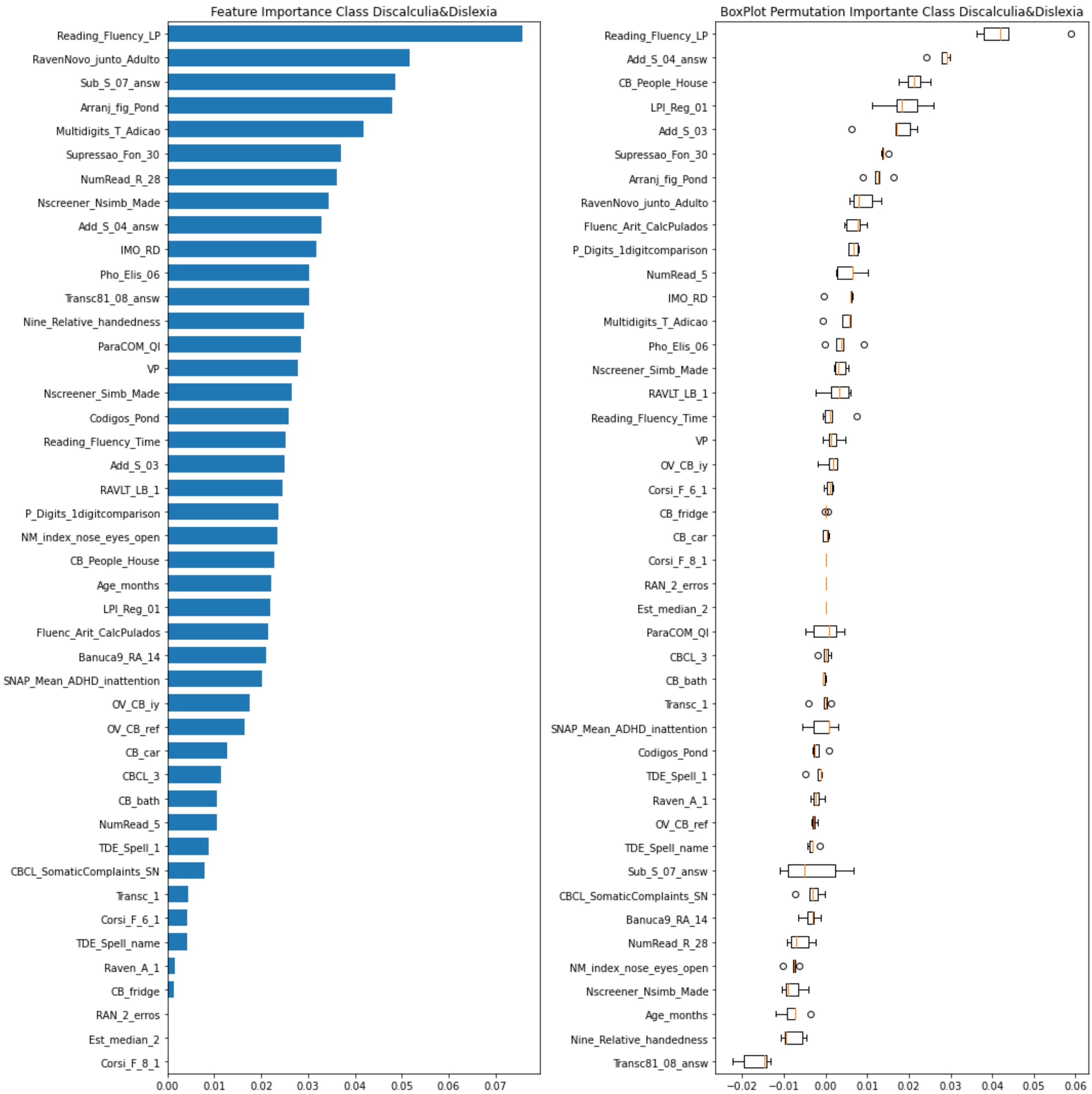


Figure 20 – Dataset762 : Variable Importance of Class Dyscalculia and Dyslexia.

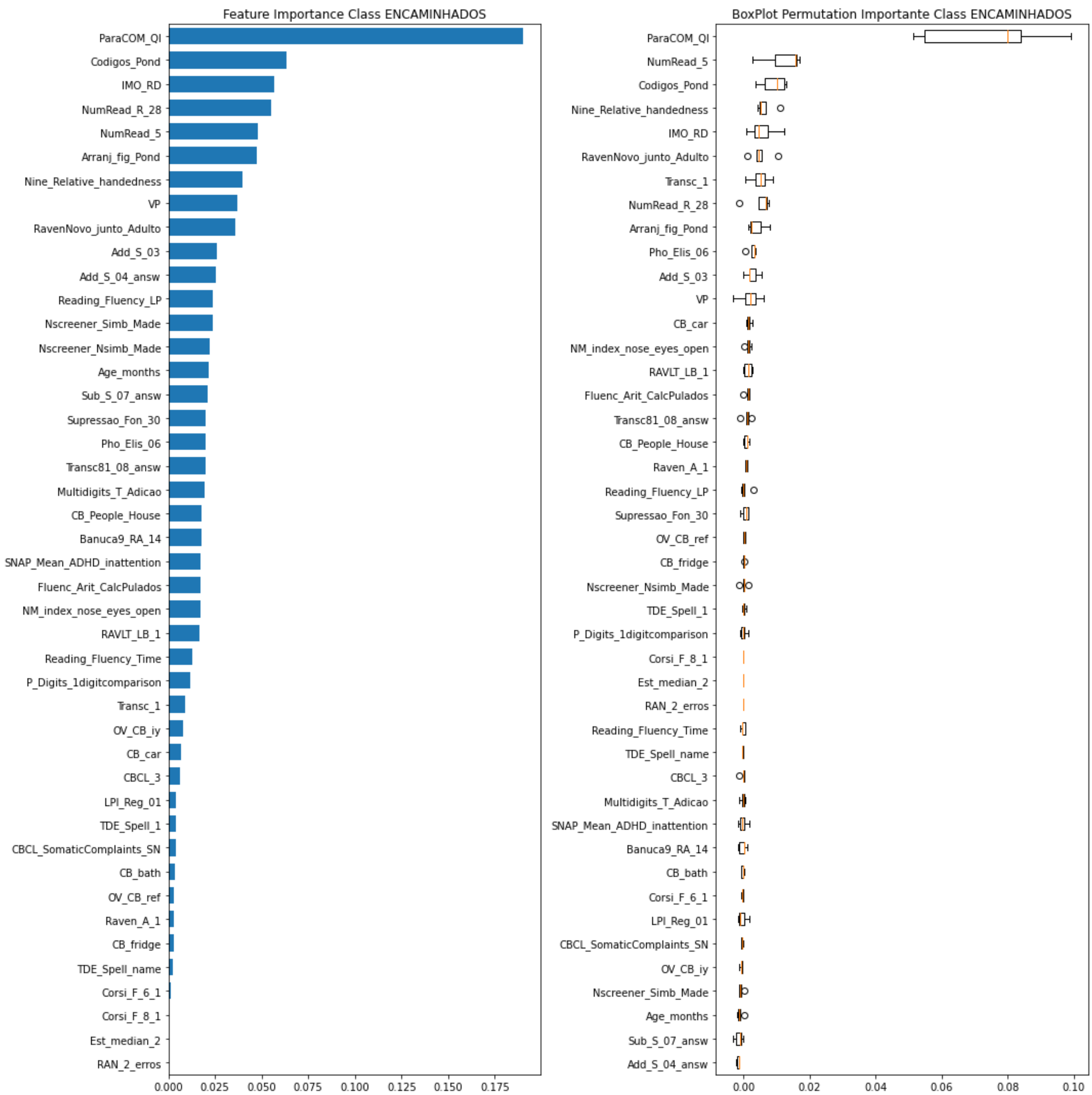


Figure 21 – Dataset762 : Variable Importance of Class *Encaminhados*

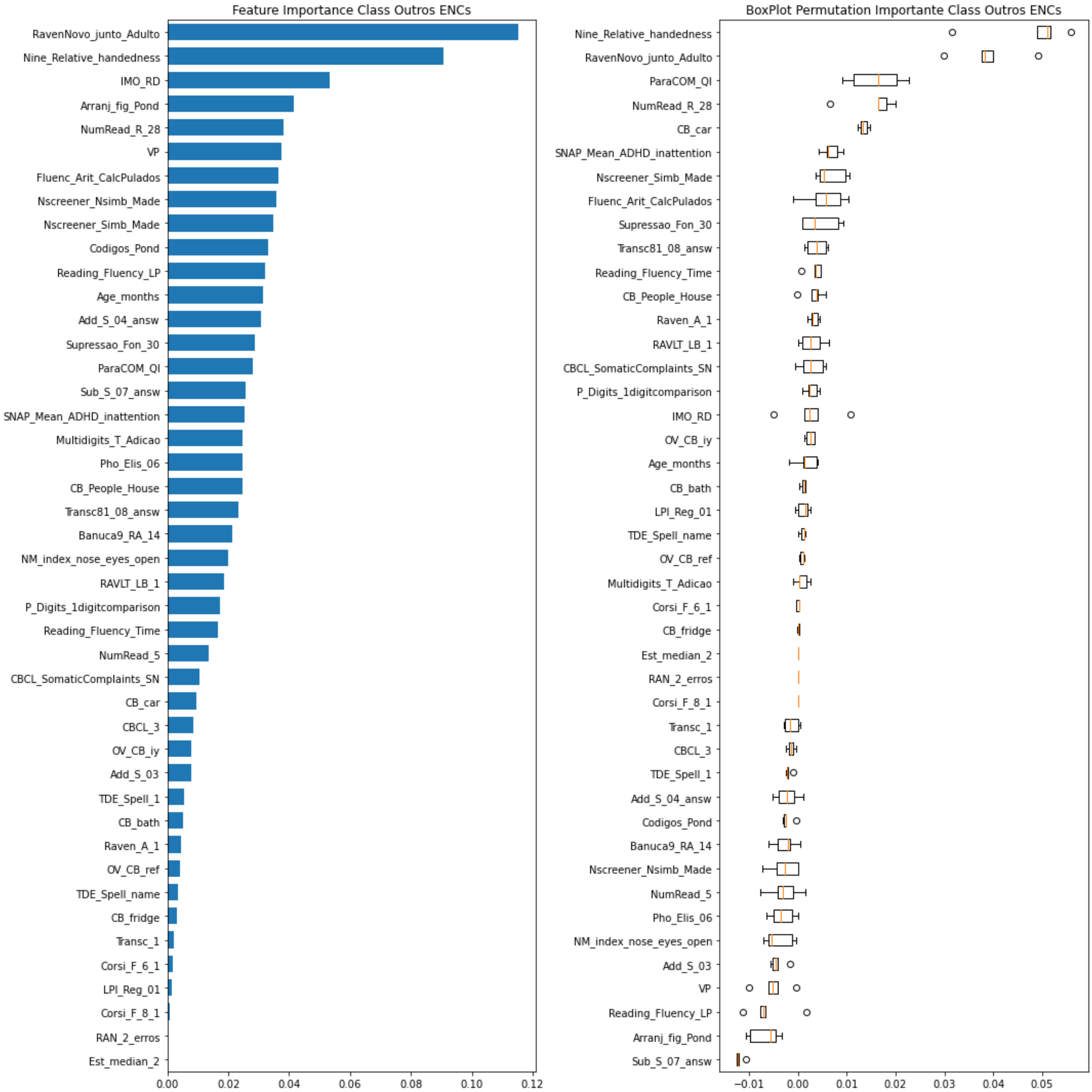


Figure 22 – Dataset762 : Variable Importance of Class *Outros Encaminhados*

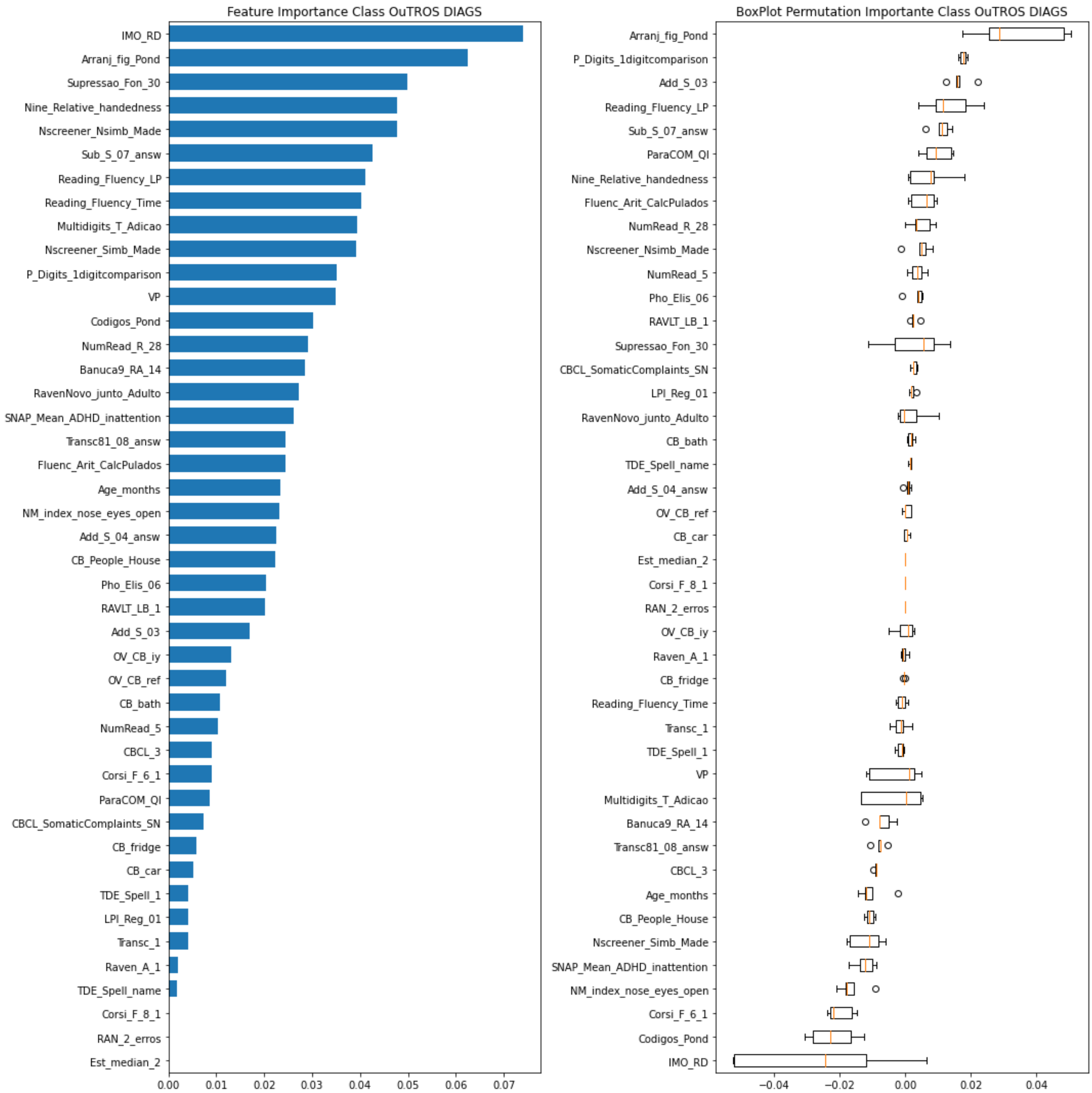


Figure 23 – Dataset762 : Variable Importance of Class Other Diagnoses

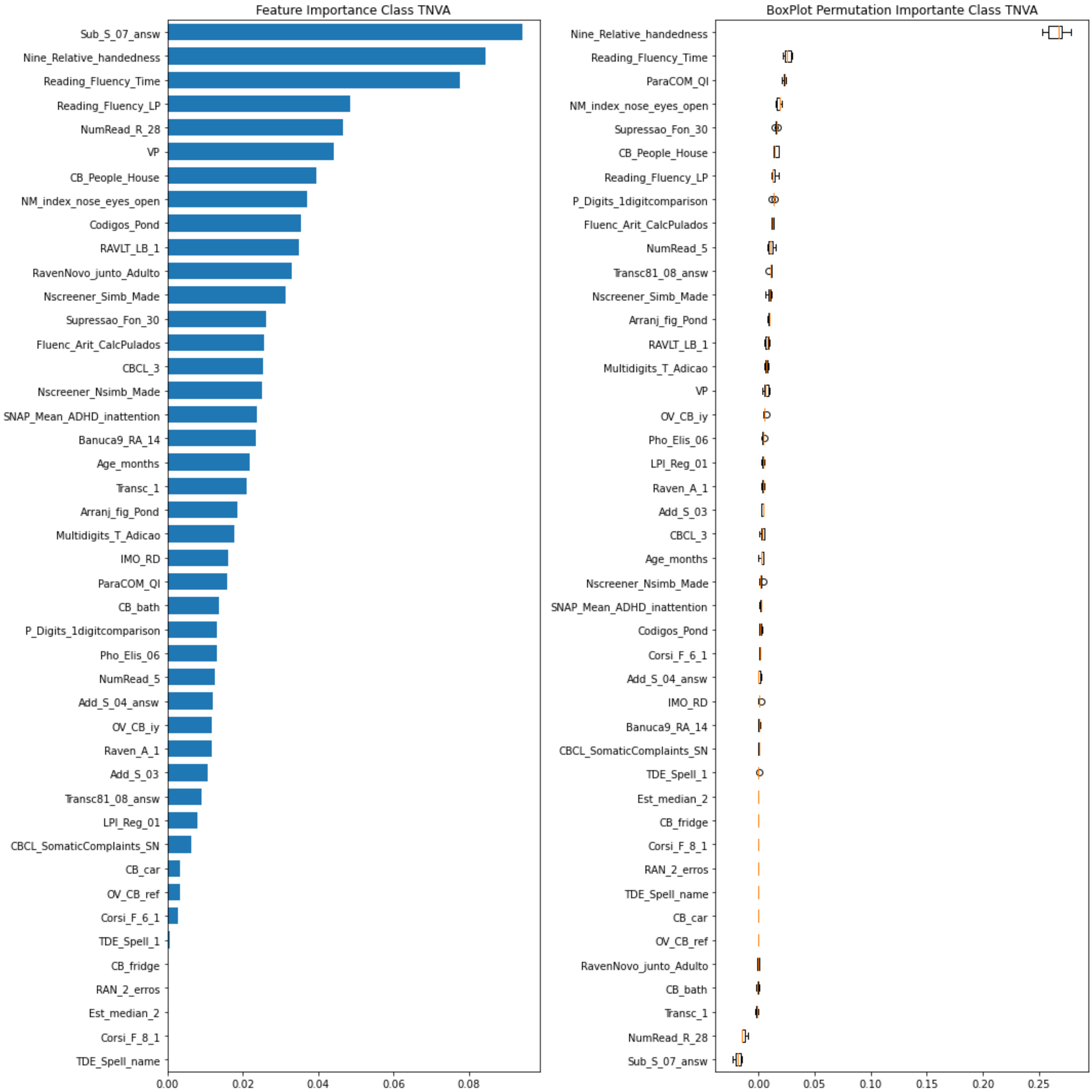


Figure 24 – Dataset762 : Variable Importance of Class NLD

4.4 Practical Use

The proposed framework can be applied to any dataset containing high number of variables, with mixed data types (continuous and categorical), and multiple classes, since eligible for supervised machine learning. Typically, psychometric tests from diverse specialization areas are formatted like this. In this section we present two possible manners of framework application with practical examples, as it follows described.

4.4.1 Hybrid Feature Reduction

In this section we advocate that our hybrid framework is able to select a valid group of variables in order to classify adequately the diagnoses groups, in terms of performance, as showed in ROC curve for each data set (Fig.45, Fig.52, Fig.60, Fig.18) and Tab.6.

Resulting from variable reduction, we found decreasing complexity in every term of comparison with achieved dimensionality reduction. On the other hand, the Dataset149 appears to be most complex dataset and less appropriate to learn from, since even after cluster selection, its density parameters $D_i < 1$ (OSHIRO; PEREZ; BARANAUSKAS, 2012).

In Tab.12 we present complexity comparison from before and after selecting the best threshold for each data set. When it is mentioned bellow $t = 0$, the original data set composition is refereed.

Table 12 – New data set Complexity Analysis - After thresh old cluster cut selection

Name	t	$\|D\|$	$\|X\|$	$\|Y\|$	***CPLX***	***D1***	***D2***	***D3***
Dataset762	0	762	1568	6	7E+06	0.90	0.66	0.64
Dataset762	1.6	762	44	6	2E+05	1.75	1.28	1.24
Dataset364	0	364	1572	5	3E+06	0.80	0.58	0.56
Dataset364	1.4	364	64	5	1.1E+05	1.42	1.03	0.99
Dataset149	0	150	1569	4	9E+05	0.68	0.49	0.46
Dataset149	0.5	150	501	4	3E+05	0.79	0.57	0.54
Dataset083	0	81	1560	3	4E+05	0.60	0.45	0.41
Dataset083	2.44	81	27	3	6.6E+03	1.34	1.0	0.92

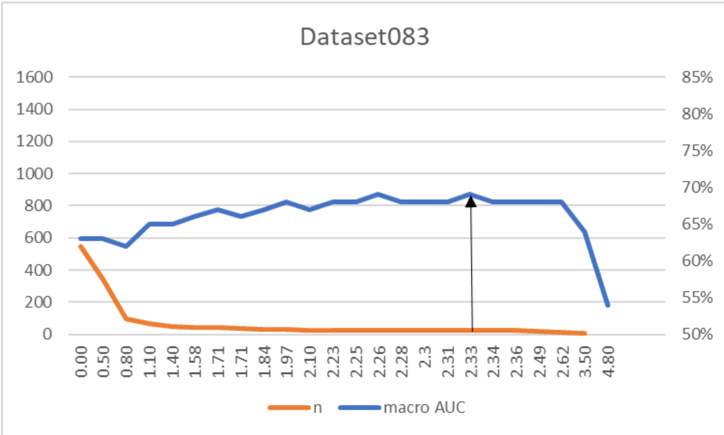
4.4.2 Analyses and Proposal For New Psychometric Instruments

As another possible product from the framework application, we refer in this section to a more compact protocol, to be built based on the leader variables of the formed clusters. As we may see in Tab.6, the selected variables can be used to build a RF model capable for dyscalculia and others learning disabilities classification, with high performance. Nevertheless, to build a new psychometric tool based on the reduced models presented, the specialists should analyze the leader variables capability and independence, before we confirm the proposed instrument viability.

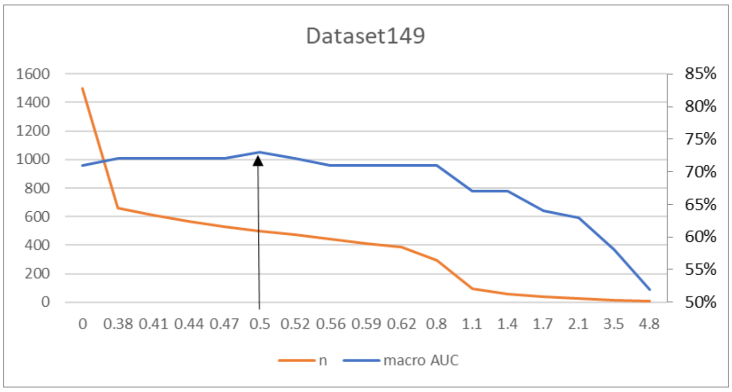
The following figures show classifiers' macro average and variable number behavior during framework execution, while diverse threshold cuts are analyzed. It is important to notice that framework parameters (δ and initial T vector) influence the final threshold selection.

Comparing those evolution graphics in Fig.25a, Fig.25b, Fig.25c and Fig.25d is possible to observe that the framework was able to suggest smaller models (lower number of variables) with better performance results although keeping higher number of outliers.

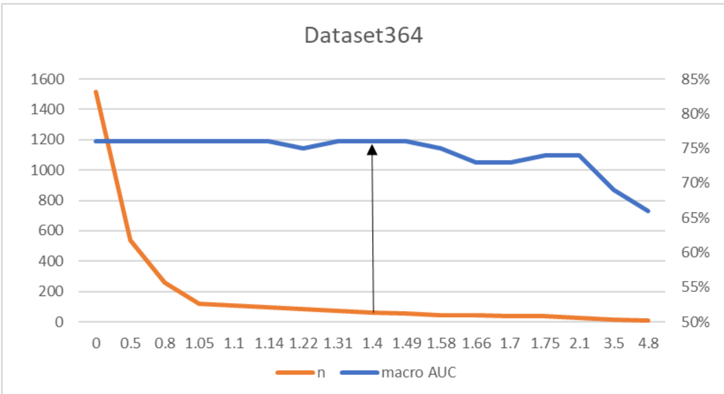
Although Dataset149 results' decreases in terms of performance, as the sample size decreases, the evolution curve shows a different behavior in its beginning and ending phases. As mentioned before, when Tab.12 was discussed, it was expected some difficulties due to data set higher complexity and lower density. Thus, Dataset149, with 4 classes, has the higher number of variable selection, while it presents no outliers on box plot for each of its 4 laps demanded to achieve the final threshold. This details can also be observed on Tab.6. This behavior differences imply some interesting characteristic on diagnose protocol to be investigated, considering dataset149 data collection occurs in the middle of diagnosis process shown at Fig. 7.



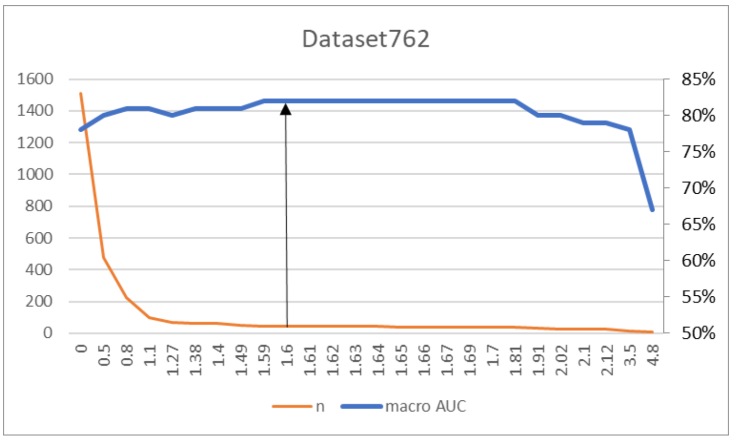
(a) Dataset083 evolution plot



(b) Dataset149 evolution plot



(c) Dataset364 evolution plot



(d) Dataset762 evolution plot

Figure 25 – Performance evolution based on performance of RF models over data sets, according t values selection. The arrow shows the best t selected, according framework parameters (δ =0.03 and initial T vector).

5 Conclusions

Our framework addresses the challenge of diagnosing a diverse range of learning disabilities by employing a multiclass approach. This enables accurate classification and characterization of different learning disorders within a single framework. Specially, Random Forest is a suitable for multiclass classification due to its ability to handle the hierarchical characteristics of NUMERO diagnosis protocol.

By incorporating variable reducing analysis, we enhance the diagnostic efficiency of the psychometric protocol. This reduction analysis helps identify the most relevant variables, streamlining the diagnostic process and eliminating irrelevant factors. Moreover, high dimensionality combined to small sample size is a common and prevalent feature of learning disorders data sets. Therefore, this challenging problem is treated by variable reduction in this work.

As a differential, the framework results integrates clinical evaluation alongside psychometric analysis to develop a singular diagnosis classifier, intrinsically provided by NUMERO data set. The source database utilized in this study was obtained from a real diagnosis protocol, encompassing data from clinical evaluations of patients. It means that some psychometrics results in the ENI phase were overlap by clinical evaluation causing possible data noise, in the machine learning point of view. This feature, associated with high missing rates database, makes important the choices of missing values combined solutions. This characteristic differs from other studies in the literature that predominantly rely solely on psychometric tests. This holistic approach ensures a comprehensive and accurate diagnosis that considers both clinical observations and objective psychometric data.

Nevertheless, the multiclass approach employed in this research enables the evaluation of joint diagnoses variables and subsequent analysis of their importance for each diagnosis class. This approach facilitates the comparison of the influential effects of the selected variables during the classifier assembly process and their impact on the classification error for each specific diagnosis class. By examining the variables' importance and their relationship to classification errors, we gain valuable insights into the significance of these variables for accurate and comprehensive diagnosis.

Furthermore, the framework provides insights into the core deficits associated with learning disabilities by leveraging variable ranking analysis. This analysis helps identify the key variables that contribute significantly to the diagnostic classification, enhancing our understanding of the underlying mechanisms of these disorders. As different variables perform different roles in learning disorder diagnosis, therefore, it is crucial to generate a comparative ranking variable for each specific class.

We identify several possible future works from the study regarding parameters of execution of the classifiers that followed an established pattern without no proper exploration. Also, statistics tests should be complemented with more complete versions of Bonferroni, as Holm´s proposition.

Moreover, combined classification models or supervised hybrid techniques classification could be used to increase performance of classification. Complementary, a multi-label approach will be considered in future work, since it describes even more adequately multiple symptoms overlap subject for learning disorders.

In addition to those technical opportunities, based on the protocol presented in Fig.7, other subsets of data with additional diagnoses classes could be extracted for comparative analyses between sections of the same protocol, through the application of the framework suggested. Also, psychometrics protocols applicable to other learning disabilities could be submitted to equivalent analyses.

Overall, we believe that our approach has the potential to advance the diagnosis and understanding of learning disabilities, including DD and comorbidity, while providing a framework that can be adapted to various other learning disorders.

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Appendix

A

About Tools Applied

A.1 Python

We deployed Python version 3.9 to develop all functions from extracting data sets till framework development. We also utilized the available Pandas and Numpy tools among others :

- import pandas as pd
- import numpy as np
- import matplotlib.pyplot as plt
- import re
- import nltk
- import string
- import math
- from collections import defaultdict

A.2 ScikitLearn

The following classes from Scikit-Learn 1.1.2 were implemented in this dissertation:

- from sklearn.inspection import permutation_importance
- from sklearn.multiclass import OneVsRestClassifier
- from sklearn.metrics import roc_auc_score

- from sklearn.model_selection import RepeatedStratifiedKFold
- from sklearn.ensemble import RandomForestClassifier
- from sklearn.impute import KNNImputer
- from sklearn.preprocessing import label_binarize
- from sklearn.preprocessing import LabelEncoder
- from sklearn.preprocessing import StandardScaler, OneHotEncoder
- from sklearn.impute import SimpleImputer
- from sklearn.pipeline import Pipeline
- from sklearn.datasets import fetch_openml
- from sklearn.compose import ColumnTransformer
- import sklearn.neighbors._base
- from sklearn.svm import SVC

A.3 Imbalanced-Learn

Imbalanced-learn is a python package offering a number of re-sampling techniques commonly used in data sets showing strong between-class imbalance. It is compatible with scikit-learn.

- import imblearn

A.4 Scipy

The following classes from Scipy 1.9.1 were implemented in this dissertation:

- import scikit_posthocs as sp
- from scipy.spatial.distance import squareform
- from scipy.cluster import hierarchy
- from scipy.stats import spearmanr
- from scipy.stats import friedmanchisquare

- from scipy.stats import wilcoxon
- from scipy.stats import rankdata

A.5 Orange

From Orange 3.30 we implemented classes to CD calculation and plots, as :

- from Orange.evaluation import compute_CD, graph_ranks

A.6 MissForest

MissForest is a supervised machine learning that imputes missing values using RF in an iterative mode. Proposed by Stekhoven (2012), the method predicts the missing values using a RF trained on the observed parts of the dataset(STEKHOVEN; BUHLMANN, 2012).

Starting with an initial guess for missing values, it trains and fits RF method column by column as predictors and response, from column with minor missing values until the last one. Meanwhile it calculates the difference between imputed arrays over successive executions, until the difference increases for the first time. Therefore, after achieving the stopping criteria the algorithm is able to assess the performance of the estimation by comparing the true imputation error (averaged error over the set of variables) with OOB error estimated at each variable fitting process.

MissForest showed to outperform the well-established imputation method KNN (STEKHOVEN; BUHLMANN, 2012). Therefore, Stekhoven states that it can handle multivariate data consisting of categorical and continuous variables, and its full potential is deployed when more complex interactions and relations between variables takes place, thus with high dimensionality.

To deploy MissForest algorithm in this dissertation, we utilized the following package available :

- from missingpy import MissForest

B

About Baseline Techniques

B.1 Spearman Correlation

The Spearman's test is a non-parametric test of bi-variate correlation coefficient, meaning it examines whether two variables are correlated with one another or not. The Spearman's test can be used to analyze ordinal level, as well as continuous level data, because it uses ranks instead of assumptions of normality. The Spearman's rank-order determines the strength and direction of the monotonic relationship between two variables measured at ordinal, interval or ratio level. The test will yield a figure of between -1 and +1, and the closer the figure is to 1, the stronger the monotonic relationship.

$$r = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

$$\begin{aligned} r &= Spearman`s\ rank\ correlation\ coefficient \\ d &= difference\ between\ two\ variable\ ranks\ of\ each\ example \\ n &= number\ of\ examples \end{aligned}$$

To apply HCA we firstly obtain the distance matrix, a non-negative, square, symmetric matrix based on the Spearman correlation matrix. Some usefully corrections are necessary without interfere in the expected results, in order to obtain the dissimilarity measure between all variables. Since correlation measures similarity, it needs to be transformed in a way such that 0 correlation is mapped to a large number, while 1 correlation is mapped to 0. On Python command line: $distance\_matrix = 1 - np.abs(corr)$.

B.2 Suport Vector Machine (SVM)

The Support Vector Machine (SVM) is a supervised machine learning technique that aim to find a hyperplane that effectively separates the classes in their training data by maximizing the margin between the outermost data points of each class. If the data is not linearly separable in the original feature space, a non-linear kernel parameter can be set, making it compatible to quadratic, polynomial and beyond. SVM is an extremely competent linear classifier, while it can deal with any type of data and is effective in high dimensional spaces, for binary classification.

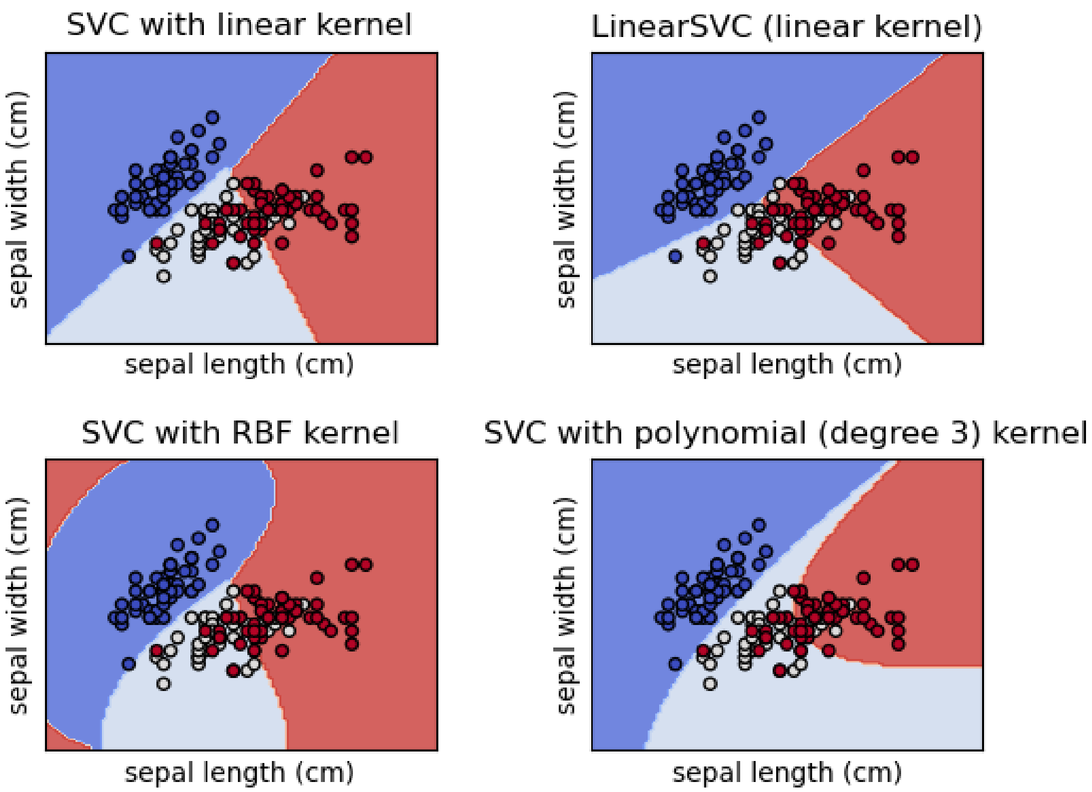


Figure 26 – SVM examples with different kernel methods. Figure from scikit-learn (AL., 2011)

Here we considered applying the radial basis function kernel, which is the standard kernel for sklearn model, during preliminary tests. Furthermore, for this multiclass implementation we combined *sklearn.svm.SVC* (support vector machine classification) with an one-vs-all solution available at scikit learn *OneVsRestClassifier*. This strategy consists in fitting one SVC classifier per class, against all the other classes.

C

About Numero Protocol

In this section we briefly address the protocol followed at the Number Outpatient Clinic, of the School of Psychology - UFMG, for the diagnosis of developmental dyscalculia and comorbidity. The diagnosis protocol followed at Number Outpatient Clinic for DD and comorbidity is composed of two hierarchically organized phases:

- Phase I: Initial Neuropsychological Examination (ENI). In this first moment, patients are screened. Interviews are conducted with family members and semi-structured questionnaires (anamnesis, among others) are filled out to rule out complications of another nature and identify referral needs. Patients are submitted to the initial neuropsychological examination for the elaboration of the diagnostic hypotheses by the clinical team. The exam consists of several instruments: CBCL (Child Behavior Checklist), SNAP-IV (ADHD Screening Questionnaire), QAM (Mathematical Anxiety Questionnaire), MPC (Raven's Colored Progressive Matrices), MP (Raven's Progressive Matrices), WISC-V (Wechsler Scales for Intelligence Assessment) and TDE (School Performance Test). All the instruments mentioned are composed of several questions or tasks for execution that are evaluated according to criteria established individually for each instrument. Clinical evaluation criteria are also considered for the referral from the ENI phase to the ENC, and the clinical criterion may overlap with the psychometric results.

- Phase II: Complete Neuropsychological Assessment (CNS). In the first stage of this phase, evaluations of general domains and of the patient's reading and writing skills are made. The instruments used are: 9-HPT (Nine-hole Peg Test), TRS (Simple Reaction Time), Rey Complex Figure, Corsi Cubes, Digit span, FDT (Five Digit Test), Phoneme Suppression Task, LPI (Reading of Isolated Words), Reading Fluency, TELCS (Reading Test: Sentence Comprehension). The second stage is performed the specific assessment and mathematical skills, with the following assessment instruments: Comparison of symbolic and non-symbolic magnitudes, Point

Estimation Task, Number Reading Task and the PRONUMERO Battery composed of TTN (Numerical Transcoding Task), TCAB (Basic Arithmetic Calculations Task) and TPAN (Narrative Problems Task).

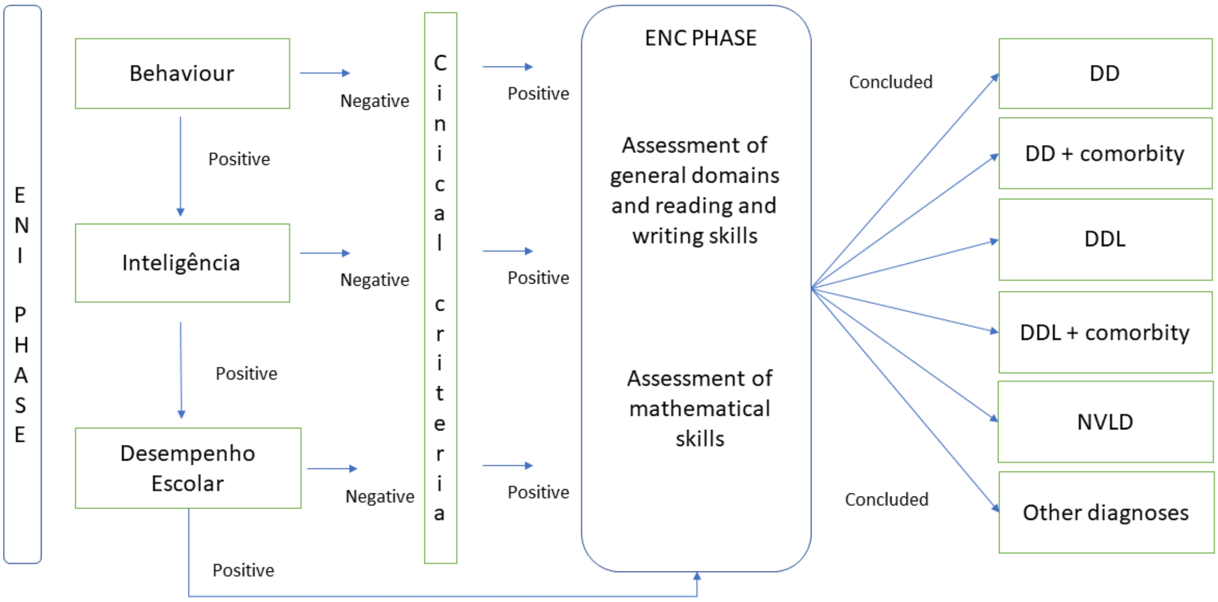
Each psychometric instrument follows its own rules of application, analysis objectives, criteria and its composition vary in terms of the number of questions and subtests performed. Besides psychometric results, clinical evaluation are considered for the referral of the ENI phase to ENC, and the clinical criterion may overlap with psychometric ones.

Figure 27 – Protocol Instruments from LND-UFMG

	Function	Composition
Instruments STAGE I		
CBCL(Child Behavior Checklist)	psychiatric disorders	113 questions
SNAP-IV(ADHD screening)	ADHD screening	26 items
MAQ(Math Anxiety Questionary)	behavioral	24 questions
MP(Progressive Matricess)	non-verbal reasoning	36 items
RCPM(Raven Colored Progressive Matrices)	non-verbal reasoning	60 items
WISC-V(Weschler Intelligence Scale)	verbal and non-verbal reasoning	unique
TDE(School Performance Test) - arithmetics subtest	School performance of arithmetic 2nd to 7th grade	48 questions
TDE(School Performance Test) - writing subtest	School performance of writing 2nd to 7th grade	34 questions
TDE(School Performance Test) - reading subtest	School performance from reading 2nd to 7th grade	70 questions
Instrumentos ETAPA II - Avaliação de domínios gerais e da habilidades de leitura e escrita		
9-HPT(Nine-hole Peg Test)	motor skills	unique
TRS (Simple Reaction Time)	attention by motor reaction	unique
Rey Complex Feature	visuospatial skills	unique
Corsi Cubs	working memory and visuospatial short-term	unique
Digit Span	working memory and verbal short-term	unique
FDT (Five Digit Test)	executive functions	4 subtests
Phoneme Suppression Task	phonemic awareness	28 items
LPI (Single Word Reading)	reading-related skills	unique
Reading Fluence	reading-related skills	unique
TELCS (Reading Test: Sentence Comprehension)	reading-related skills	unique
Instrumentos ETAPA II - Avaliação das habilidades matemáticas		
Comparison of symbolic magnitudes	symbolic representation	unique
Comparison of non-symbolic magnitudes	symbolic representation	unique
Point Estimation Task	approximate number system	35 questions
Number Reading Task	math skills	unique
PRONUMERO Battery - TTN (Numerical Transcoding Task)	math skills	81 questions
Battery PRONUMERO - TCAB (Basic Arithmetic Calculations Task)	math skills	82 questions
PRONUMERO Battery - TPAN (Narrative Problems Task)	math skills	12 questions

The path of each patient throughout the diagnostic process determines the hierarchical characteristic of the resulting data set. Starting in the ENI phase, patients whose psychometric results and clinical evaluation indicated compliance with the criteria of the diagnostic hypothesis, followed the process to the ENC phase, as outlined in the following figure.

Figure 28 – Protocol Process Flow from LND-UFMG



DD : Learning Disorder with Mathematics Impairment
DL : Learning Disorder with Reading Impairment
DDL : Learning Disorder with Impairment of Reading, Writing, and Math
NVLD : Nonverbal Learning Disorder

D About Intermediate Results

The first stages of tests were conducted to understand the preliminary performance of models. We chose to compare multiclass RF with multiclass OVR RF and SVM classifier, discussed better in Appendix B.

D.1 Use of OneHotEncoder and KNN in preprocessing

In those tests we performed the preprocessing with KNN method to continuous data and applied OneHotEncoder, to categorical data, on missing values treatment. AfterWards, categorical data were transformed according to cardinality with label encoder and the data sets were balanced with over sampling method. It is important to notice that on that project´s moment, some selection criterion for data sets were any different then, the instance and variable number must be not considered, but the meaning of following results.

|D|	|X|	|L|	%MISS	CPLX	D1	D2	D3
81	1843	3	51	4E+05	0,58	0,44	0,4
81	3281	3	0	8E+05	0,54	0,41	0,37
150	1853	4	55	1E+06	0,67	0,48	0,45
150	3290	4	0	2E+06	0,62	0,45	0,42
364	1864	5	62	3E+06	0,78	0,57	0,55
364	3542	5	0	6E+06	0,72	0,52	0,5
762	1861	6	68	9E+06	0,88	0,64	0,62
762	3633	6	0	2E+07	0,81	0,59	0,57

Figure 29 – Missing values on data set version

Table on Fig.29 shows missing values evolution for each data set version. Also, it is possible to understand the complexity increase when OneHotEncoder were applied, increasing the number of variables, according to its cardinality. Therefore, KNN was only permitted to numerical variables meaning that more steps in preprocess are necessary.

D.2 Preliminary comparison between all datasets

Next steps on these preliminary tests were concerning classification models comparison, where we could analyze the performance of classifiers, over RepeatedStratifiedKFold (trials=100, splits=10) to compare, as shown in Fig.30

- RandomForestClassifier(n_estimators=100)
- OneVsRestClassifier(RandomForestClassifier(n_estimators=100)
- OneVsRestClassifier(SVC(probability = True))

Furthermore, observing performance behavior a the high level of missing values, it turn out relevant to observe and understand the possibility of miss value treatment influence on model results (Fig. 31).

This led us to a question, if any variable selection reduction should increase models reliability while reducing missing values influence.

D.3 Vertical and Horizontal Comparison

We found that reducing complexity and dimensionality we could obtain better results in order to eliminate possible miss value influence. Therefore we applied HCA cuts before building models with related results in Figs. 32,33,34 and 35.

To determine each model was better we decided to apply Friedman and post-hoc Nemenyi, making pairwise comparing as shown at Fig.36.

AfterWards, we faced two possible comparison: based on graphic evolution, a vertical and horizontal analysis should be necessary, showed in Fig.37

Resuming the enhancements faced during this preliminaries tests, we can cite the following:

- Since OneHotEncoder diminished the ML approach adequacy, we considered change to LabelEncoder, based on premised of the existing ordinary relation within categorical variables.It can be used to transform non-numerical labels (as long as they are hashable and comparable) to numerical labels.
- The models performances' after variable reduction are promising.
- RF and OVR_RF performed with better performances' results for all data set after cluster selections, beyond SVM performed. It is important to notice SVM used standard *sklearn.svm* parameters, as the radial basis function kernel (rbf) in these simulations.
- In order to obtain the best cluster threshold cut, we should enable testing intervals rounding those best primarily cuts selected, without what we would not obtain the foremost performances' model.
- To designate the best classifier, we consider better using CD graphic based on Bonferroni-Dunn on future tests, instead of using Nemenyi shown in this phase. Average ranks by themselves provide a fair comparison between algorithms, so we considered simplify the computing demand, executing Bonferroni-Dunn comparison to the best classified model on average ranking. Also, Bonferroni-Dunn is able to control FWER (probability of a type 1 error is α) and its power is greater when compared to Nemenyi test (DEMšAR, 2006). The greater the test power, the minimized probability of type 2 error occurs.
- With expert support we found out a better examples selection to guarantee those hierarchical aspect suggested on Fig.7 used from this point of the project.

										RF		OVR_RF		OVR_SVM	
	|d|	|D|	|X|	|L|	%MISS	CPLX	D1	D2	D3	Mean	Std	Mean	Std	Mean	Std
Dataset083	81	135	3281	3	0	1E+06	0,61	0,47	0,44	0,971	0,031	0,967	0,032	0,96	0,036
Dataset149	150	276	3290	4	0	4E+06	0,69	0,52	0,5	0,975	0,017	0,975	0,016	0,97	0,019
Dataset364	364	1070	3542	5	0	2E+07	0,85	0,66	0,63	0,998	0,002	0,996	0,002	0,996	0,005
Dataset762	762	2388	3633	6	0	5E+07	0,95	0,73	0,71	0,998	0,001	0,998	0,001	0,991	0,004

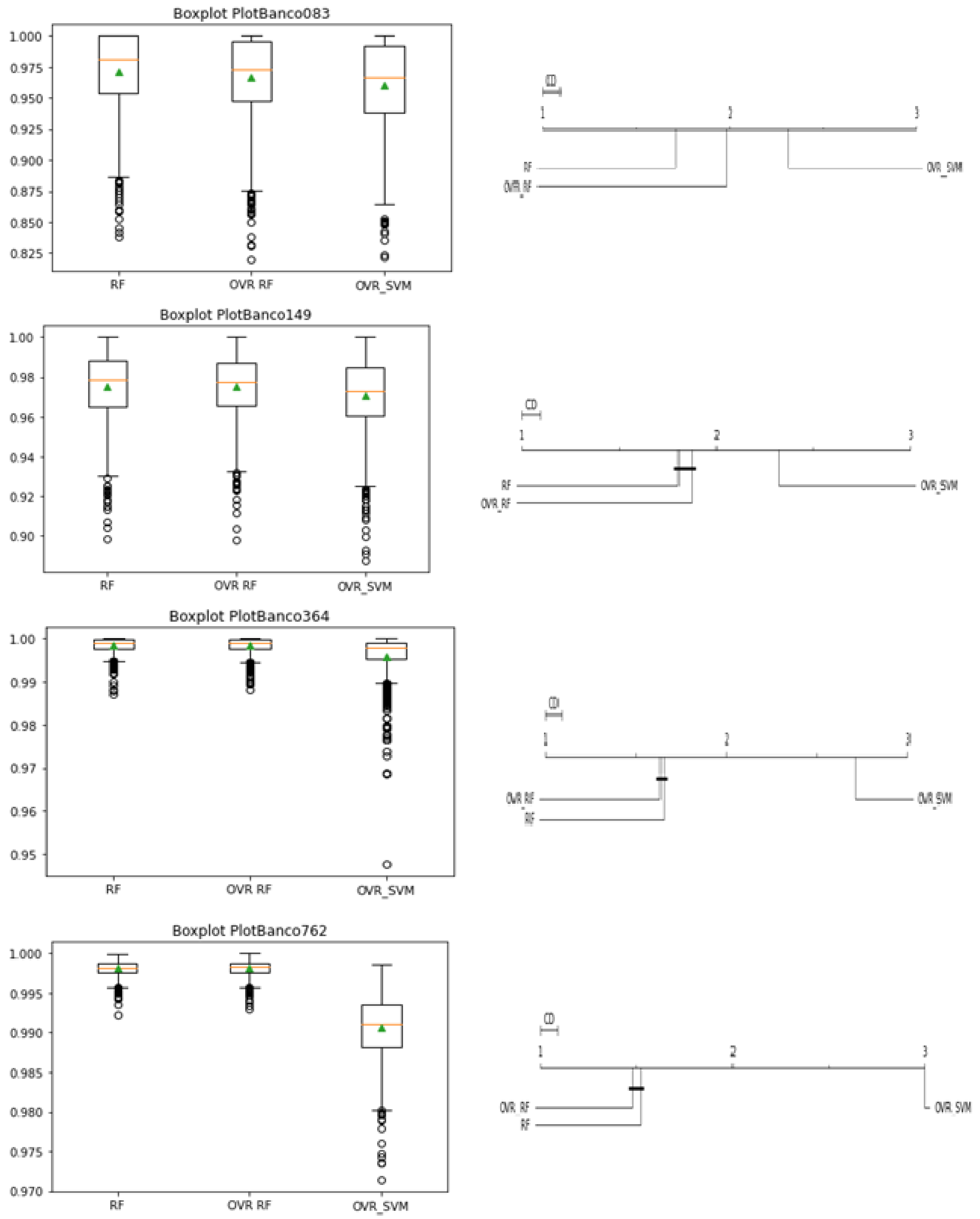
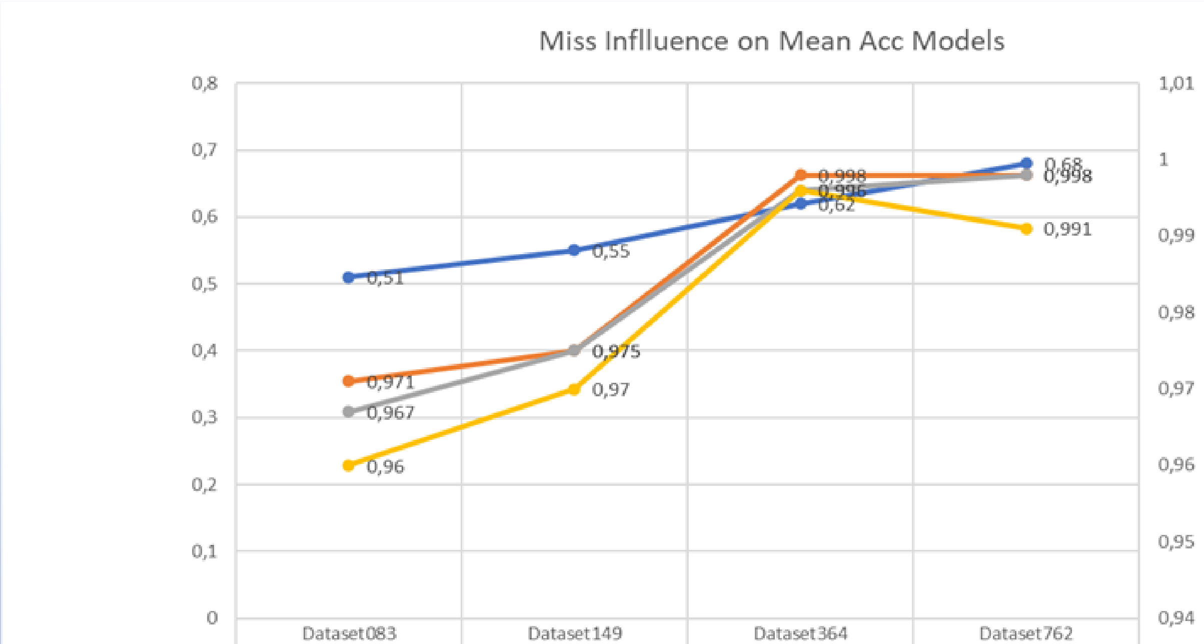


Figure 30 – Overall ML methods comparison, within all data sets. Using comparison CD graphic based on Nemenye test, we found that RF and OVR_RF perform consistently better for this application.



	Dataset083	Dataset149	Dataset364	Dataset762
MISS %	0,51	0,55	0,62	0,68
Mean RF	0,971	0,975	0,998	0,998
Mean OVR_RF	0,967	0,975	0,996	0,998
Mean OVR_SVM	0,96	0,97	0,996	0,991

Figure 31 – Missing data influence on mean performance models. During the tests we noticed the higher the initial miss value indicator, the higher the obtained performance on RF based models. Also SVM seems to be under some influence. On the other hand, the miss indicator is strongly related to dataset size, and that apparently have also some influence on performance models.

										RF		OVR_RF		OVR_SVM	
	|d|	|D|	|X|	|L|	%MISS	CPLX	D1	D2	D3	Mean	Std	Mean	Std	Mean	Std
Dataset083	81	135	2659	3	0	1,0E+06	0,62	0,48	0,45	0,974	0,032	0,970	0,033	0,961	0,039
t = 1,5	81	135	164	3	0	7,0E+04	0,96	0,75	0,69	0,986	0,024	0,981	0,026	0,969	0,033
t = 3,0	81	135	35	3	0	1,0E+04	01,38	1,07	0,99	0,982	0,027	0,978	0,028	0,959	0,415
t = 6,0	81	135	11	3	0	4,0E+03	2,05	1,59	1,47	0,938	0,054	0,939	0,053	0,863	0,080

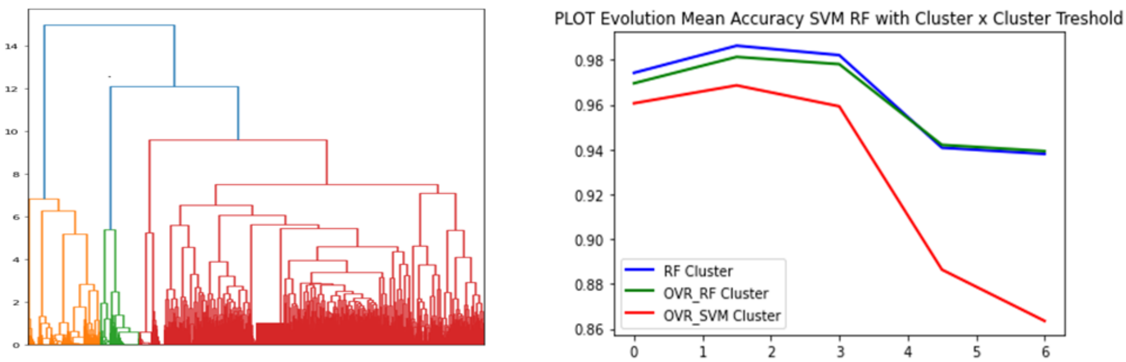


Figure 32 – Performance model dataset083 after cluster selection evolution. Evolution plot shows classifiers performance tendency when several threshold cuts were proposed on data set. Above table shows in detail the complexity parameters and related mean performance for the three best performance curve points.

	|d|	|D|	|X|	|L|	%MISS	CPLX	D1	D2	D3	RF		OVR_RF		OVR_SVM	
										Mean	Std	Mean	Std	Mean	Std
Dataset149	149	276	2705	4	0	3,0E+06	0,71	0,54	0,51	0,978	0,016	0,978	0,015	0,972	0,018
t = 1,5	149	276	159	4	0	2,0E+05	1,11	0,84	0,79	0,969	0,020	0,971	0,018	0,955	0,027
t = 3,0	149	276	34	4	0	4,0E+04	1,59	1,20	1,14	0,963	0,022	0,965	0,020	0,920	0,039
t = 6,0	149	276	13	4	0	1,0E+04	2,19	1,65	1,57	0,949	0,026	0,950	0,025	0,847	0,048

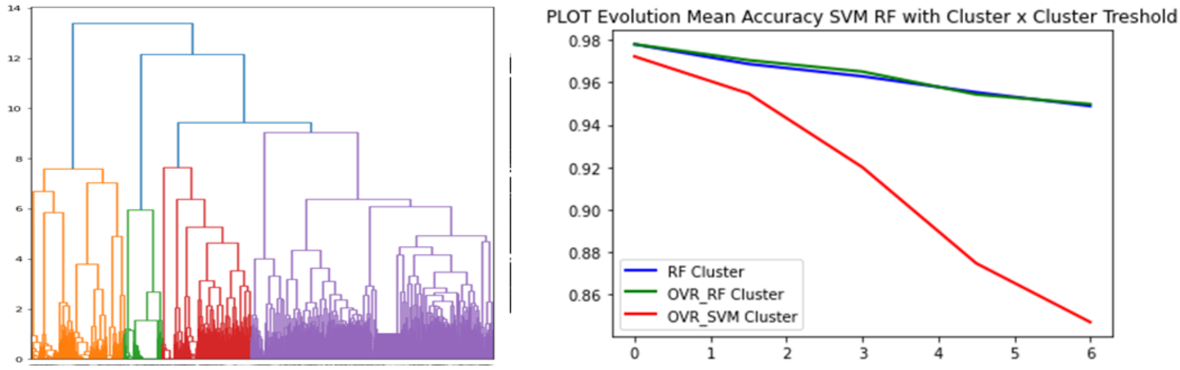


Figure 33 – Performance model dataset149 after cluster selection evolution.

	|d|	|D|	|X|	|L|	%MISS	CPLX	D1	D2	D3	RF		OVR_RF		OVR_SVM	
										Mean	Std	Mean	Std	Mean	Std
Dataset364	364	1070	3079	5	0	2,0E+07	0,71	0,54	0,51	0,999	0,001	0,999	0,002	0,999	0,004
t = 1,5	364	1070	192	5	0	1,0E+06	1,11	0,84	0,79	0,999	0,001	0,999	0,001	0,992	0,006
t = 3,0	364	1070	38	5	0	2,0E+05	1,59	1,20	1,14	0,999	0,001	0,999	0,001	0,977	0,012
t = 6,0	364	1070	12	5	0	6,0E+04	2,19	1,65	1,57	0,998	0,002	0,998	0,002	0,918	0,020

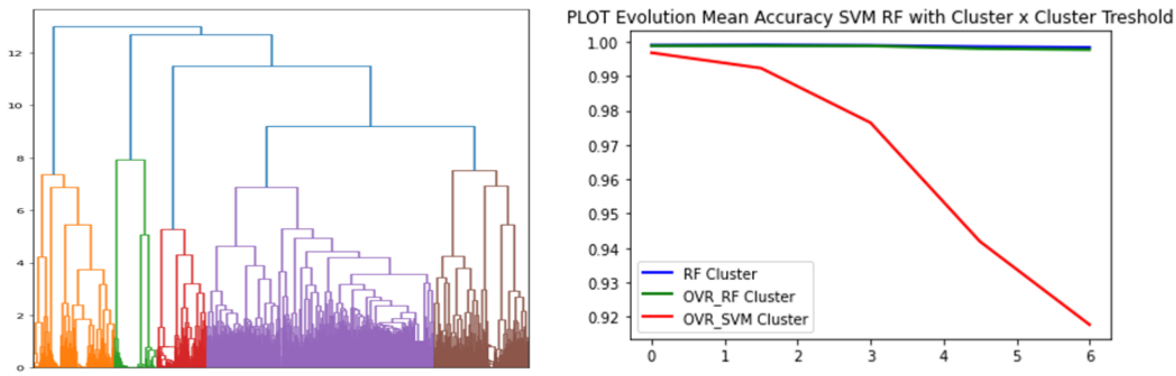


Figure 34 – Performance model dataset364 after cluster selection evolution.

	|d|	|D|	|X|	|L|	%MISS	CPLX	D1	D2	D3	RF		OVR_RF		OVR_SVM	
										Mean	Std	Mean	Std	Mean	Std
Dataset762	762	2388	3256	6	0	5,0E+07	0,96	0,74	0,72	0,998	0,001	0,998	0,001	0,990	0,004
t = 1,5	762	2388	177	6	0	3,0E+06	1,50	1,16	1,13	0,999	0,001	0,999	0,001	0,993	0,004
t = 3,0	762	2388	37	6	0	5,0E+05	2,15	1,66	1,62	0,997	0,002	0,996	0,002	0,973	0,008
t = 6,0	762	2388	13	6	0	2,0E+05	3,03	2,33	2,27	0,996	0,002	0,996	0,002	0,935	0,011

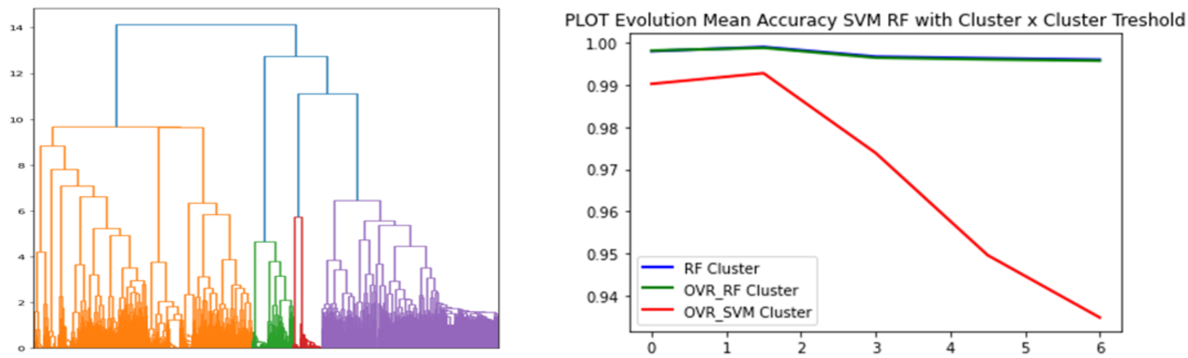
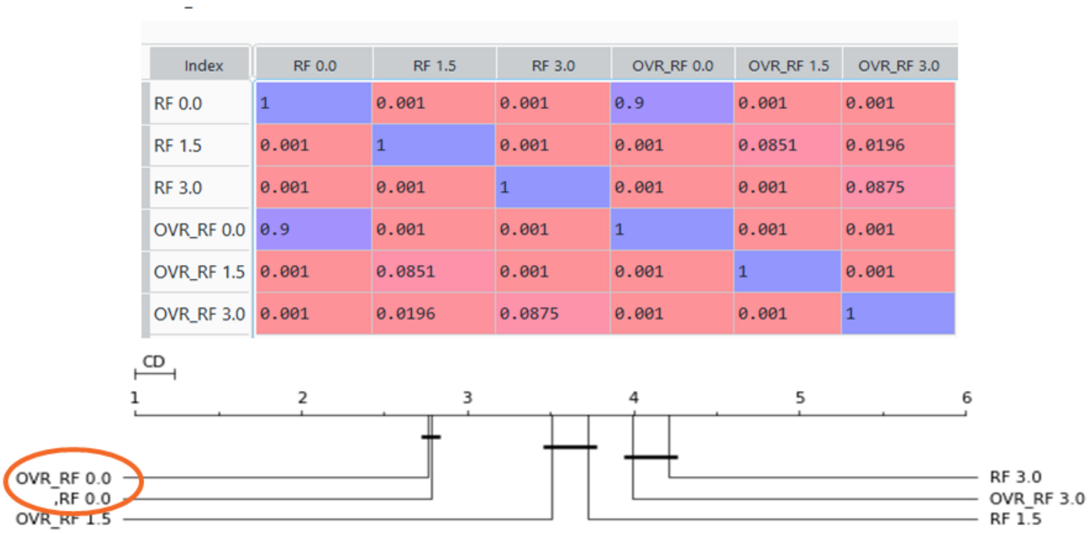


Figure 35 – Performance model dataset762 after cluster selection evolution.



Index	RF 0.0	RF 1.5	RF 3.0	OVR_RF 0.0	OVR_RF 1.5	OVR_RF 3.0
RF 0.0	1	0.001	0.001	0.9	0.001	0.001
RF 1.5	0.001	1	0.001	0.001	0.0851	0.0196
RF 3.0	0.001	0.001	1	0.001	0.001	0.0875
OVR_RF 0.0	0.9	0.001	0.001	1	0.001	0.001
OVR_RF 1.5	0.001	0.0851	0.001	0.001	1	0.001
OVR_RF 3.0	0.001	0.0196	0.0875	0.001	0.001	1

Figure 36 – Nemenyi example over threshold cuts on data set 149. The post-hoc test shows equivalence between classifiers presented as blue on table, after pairwise comparison. Whenever Friedman is executed, the p-values obtained are near by zero, when not exactly.

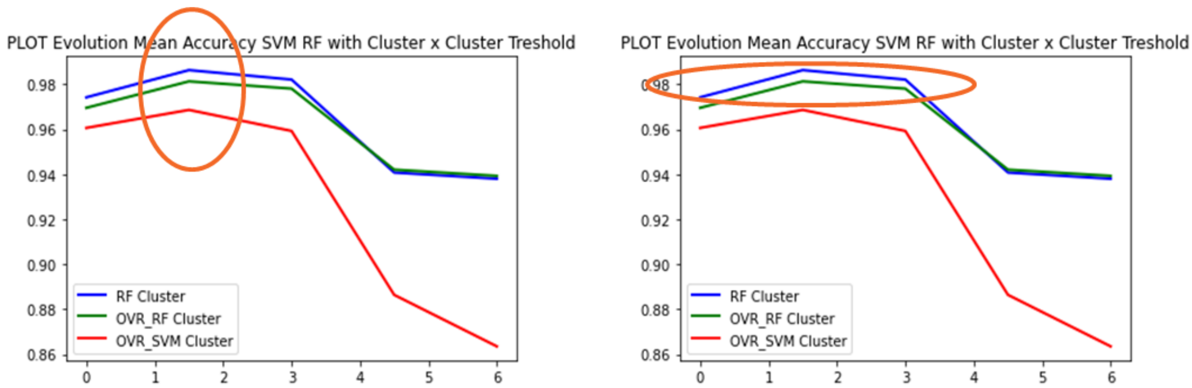


Figure 37 – Horizontal and Vertical Comparison explanation on dataset083. Red circle on both figures shows whole comparison area.

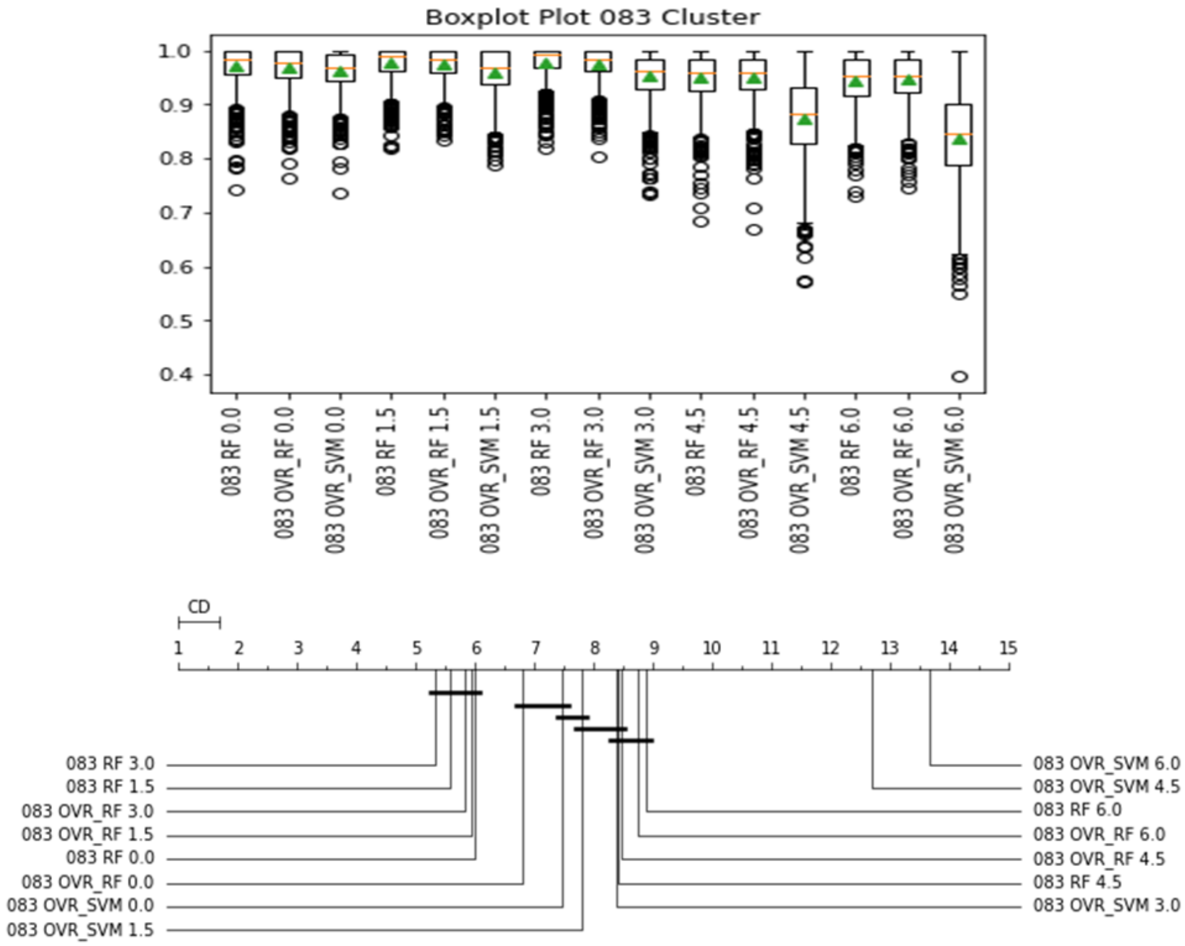


Figure 38 – Data set 083 complete comparison between selected cluster cut selections and models. CD graphic based on Nemenyi test, where all classifiers are compared to each other, shows equivalent significance between classifiers RF cluster threshold 0.0, 1.5 and 3.0, and classifiers OVR_RF, cluster threshold 1.5 and 3.0, while they are the best classifiers in terms of AUC results.

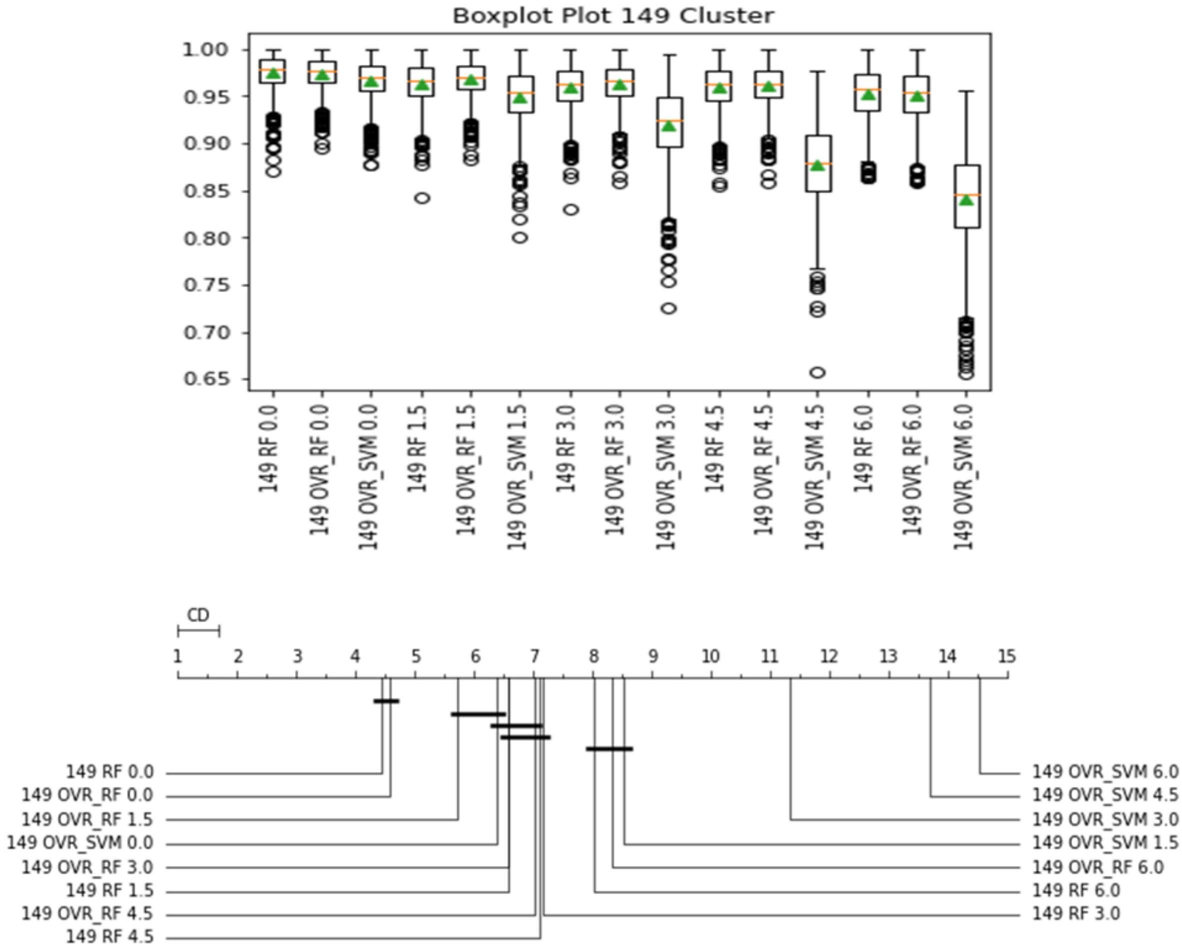
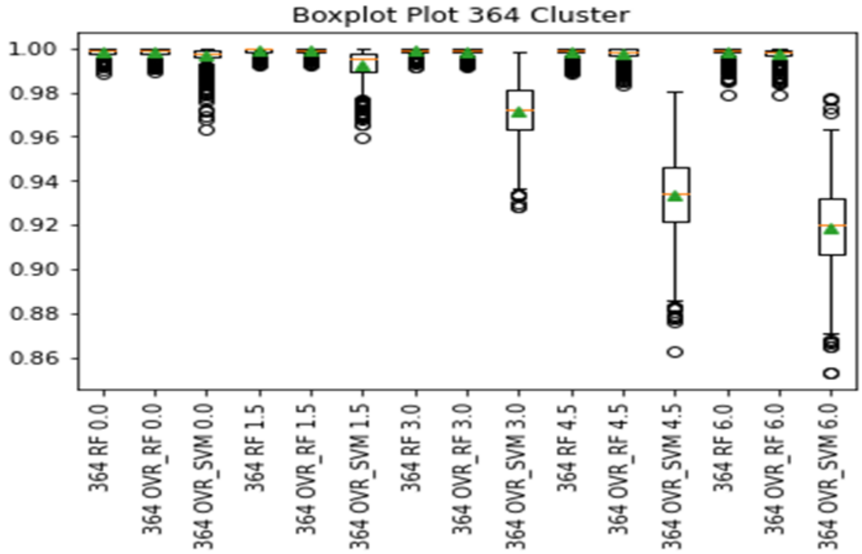


Figure 39 – Data set 149 complete comparison between selected cluster cut selections and models. CD graphic based on Nemenyi test, where all classifiers are compared to each other, shows equivalent significance between classifiers RF and OVR_RF cluster threshold 0.0, while they are the best classifiers in terms of AUC results.



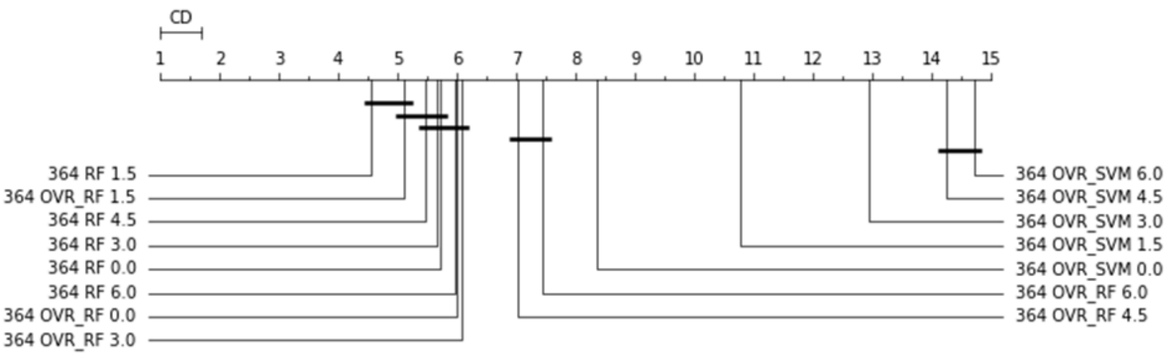


Figure 40 – Data set 364 complete comparison between selected cluster cut selections and models. CD graphic based on Nemenyi test, where all classifiers are compared to each other, shows equivalent significance between classifiers RF and OVR_RF cluster threshold 1.5, while they are the best classifiers in terms of AUC results.

E

About Algorithms

E.1 Pseudo - algorithm : Data set selection

- Require: raw database
- Upload and convert data to pandas data file
- Select data from project *Ambulatorio*
- Delete ID columns of data file
- class_col = classification column positioned as last one
- Select data file versions following Fig. 7
  - For each data file version do:
    * Delete all classification columns except last one
    * Delete all lines with null class_col
    * Delete all null columns
    * Delete all single cardinality columns
    * Calculate complexity parameters
    * Save to directory

E.2 Pseudo - algorithm : Hybrid Feature Selection

- Require: preprocessed data set, no missing values
- Extract X and Y arrays

- X ← vector of features
- Obtain Spearman rank correlation matrix for X
- Calculate HCA for X.
- Make an initial guess for cluster vector T
- T ← vector of distance threshold cut values
- While not stop criteria do
  - for t in T do
    - Obtain flat cluster indexes
    - Select subset leading variables
    - Balance subset & split test/train (50/50)
    - Repeatedly Stratify KFold
    - Fit $OVR - RF$
    - Predict probability (plot_roc) and score(roc_auc)
    - Repeat fit,predict and score for swapped train/test
    - 2-D array ← macro averaged AUC scores[t]
  - Apply Friedman/Wilcoxon tests (2-D array values)
  - Calculate average ranks and critical distance
  - Generate CD diagram(Bonferroni-Dunn)
  - T ← best ranked RF models (t respective values)
- if $|T| = 1$, T ← linspace (range based on t)
- else, T ← linspace (first t,last t)
- criteria ← update

E.3 Permutation Importance Algorithm of scikit-learn tool

The following pseudo-algorithm shows the mechanism implemented on scikit-learn, that has been utilized in this dissertation:

- Inputs: fitted predictive model, tabular training dataset.

- Compute the reference score of the model on test data (performances' for a classifier)
- For each feature (column of test dataset):
  - For each repetition in 1...K (variable cardinality):
  - Randomly shuffle column of dataset to generate a corrupted version of the dataset.
  - Compute the new score of model on corrupted dataset.
- Compute importance for shuffled feature defined as

F

Complementary results

F.1 Dataset 083

The results of framework application over Dataset083 follow in the next sections.

F.1.1 Box Plot

In this section we present box plots of framework application over Dataset083.

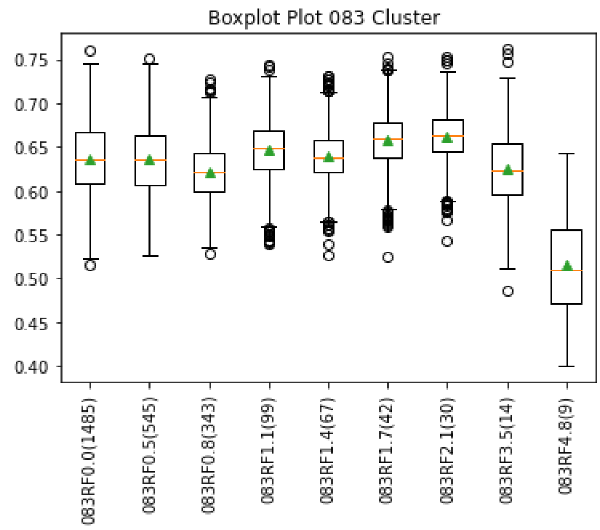


Figure 41 – Box Plot Dataset083 lap 01

Threshold (n.variables)	Outliers (by 1000)
083RF0.0(1485)	1
083RF0.5(545)	1
083RF0.8(343)	4
083RF1.1(99)	8
083RF1.4(67)	11
083RF1.7(42)	10
083RF2.1(30)	9
083RF3.5(14)	2
083RF4.8(9)	0

Table 13 – Outliers Dataset083 lap01

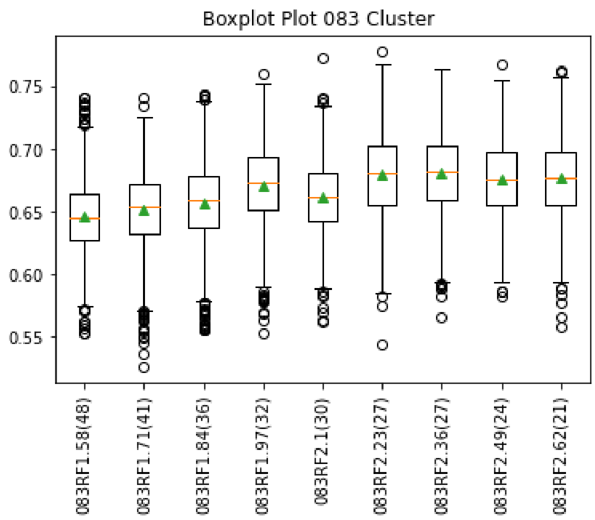


Figure 42 – Box Plot Dataset083 lap 02

Threshold (n.variables)	Outliers (by 1000)
083RF1.58(48)	12
083RF1.71(41)	11
083RF1.84(36)	7
083RF1.97(32)	9
083RF2.1(30)	10
083RF2.23(27)	3
083RF2.36(27)	3
083RF2.49(24)	6
083RF2.62(21)	4

Table 14 – Outliers Dataset083 lap02

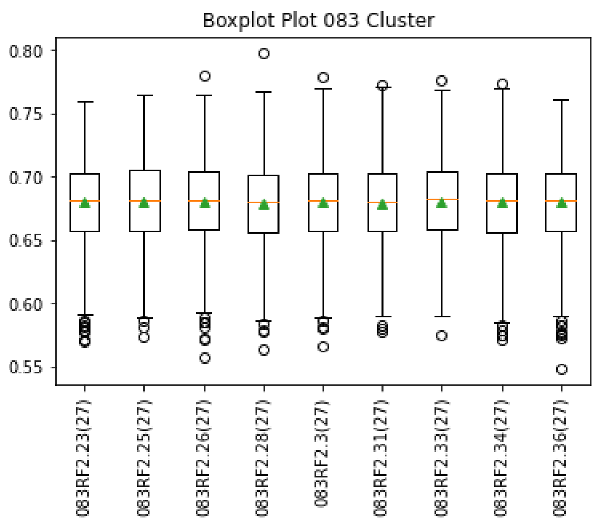


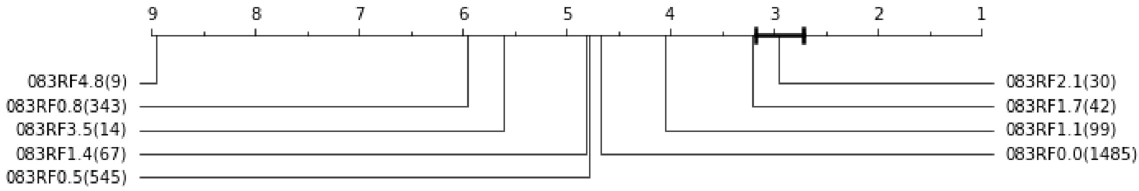
Figure 43 – Box Plot Dataset083 lap 03

Threshold (n.variables)	Outliers (by 1000)
083RF2.23(27)	3
083RF2.28(27)	4
083RF2.33(27)	3
083RF2.38(26)	3
083RF2.42(25)	1
083RF2.47(25)	1
083RF2.52(24)	6
083RF2.57(21)	3
083RF2.62(21)	1

Table 15 – Outliers Dataset083 lap03

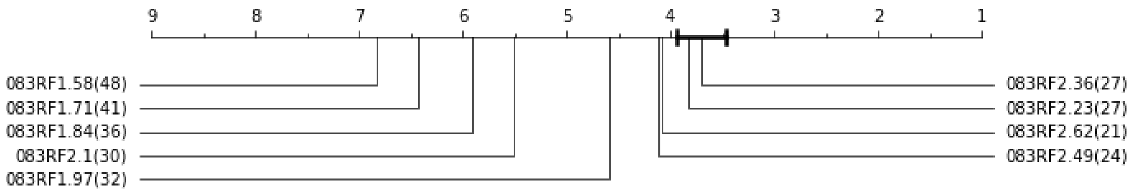
F.1.2 CD Graph

In this section we present CD graphs of framework application over Dataset083.

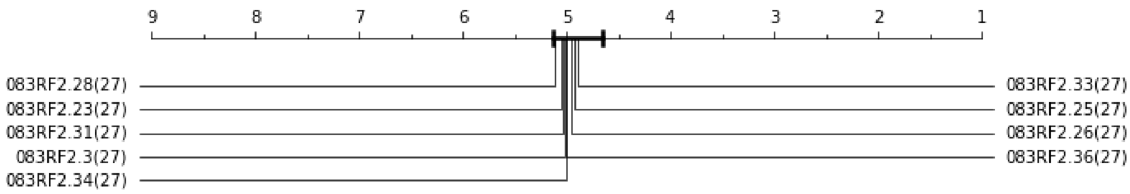


(a) CD Graph based on Bonferroni-Dunn. Best average ranked is 083RF2.1, with no equivalence to any other classifier. At this first lap, when no equivalence is achieved between models, but the distance between threshold standard $t = 0.0$ and $t = 2.1$ is bigger than $\delta = 0.03$, another lap is executed considering a new interval around best average ranked threshold, i.e. 75% as inferior limit and 125% as a superior limit

.



(b) CD Graph based on Bonferroni-Dunn. In this second lap, best average ranked is 083RF2.36, with equivalence to 083RF2.23. At this lap, as the distance between last lap threshold $t = 2.1$ and best $t = 2.36$ is more than $\delta = 0.03$, the process continues with $t = 2.23$ as inferior limit and $t = 2.36$ as superior limit.



(c) CD Graph based on Bonferroni-Dunn. In this third lap, best average ranked is 083RF2.33, with equivalence to all tested t classifiers. As a total equivalence is achieved between classifiers, the best averaged is chosen, i.e. $t = 2.33$.

Figure 44 – CD Graphs Dataset083

F.1.3 ROC Curve

In this section we present the ROC curve of framework application over Dataset083.

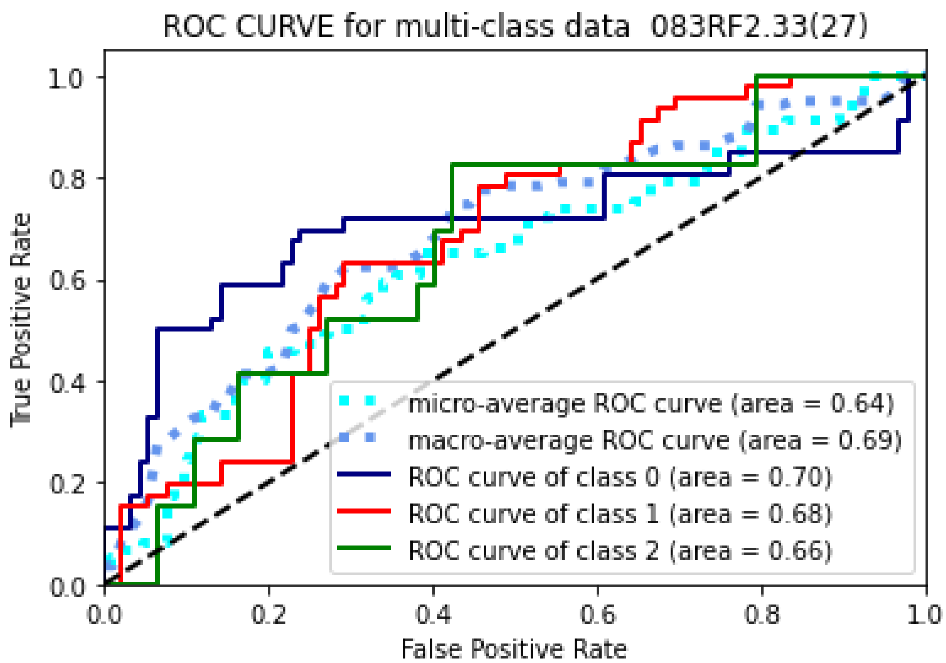


Figure 45 – Multiclass ROC Curve for best ranked RF classifier upon threshold cluster $t = 2,33$, meaning that with 27 leader variables, the model can perform the classification for diagnosis classes 0, 1 and 2 with 69% of macro average AUC. Performance for each class is shown at one-vs-rest curves.

F.1.4 Variable Importance Analyses

In this section we present the variable importance analyses plots of framework application over Dataset083.

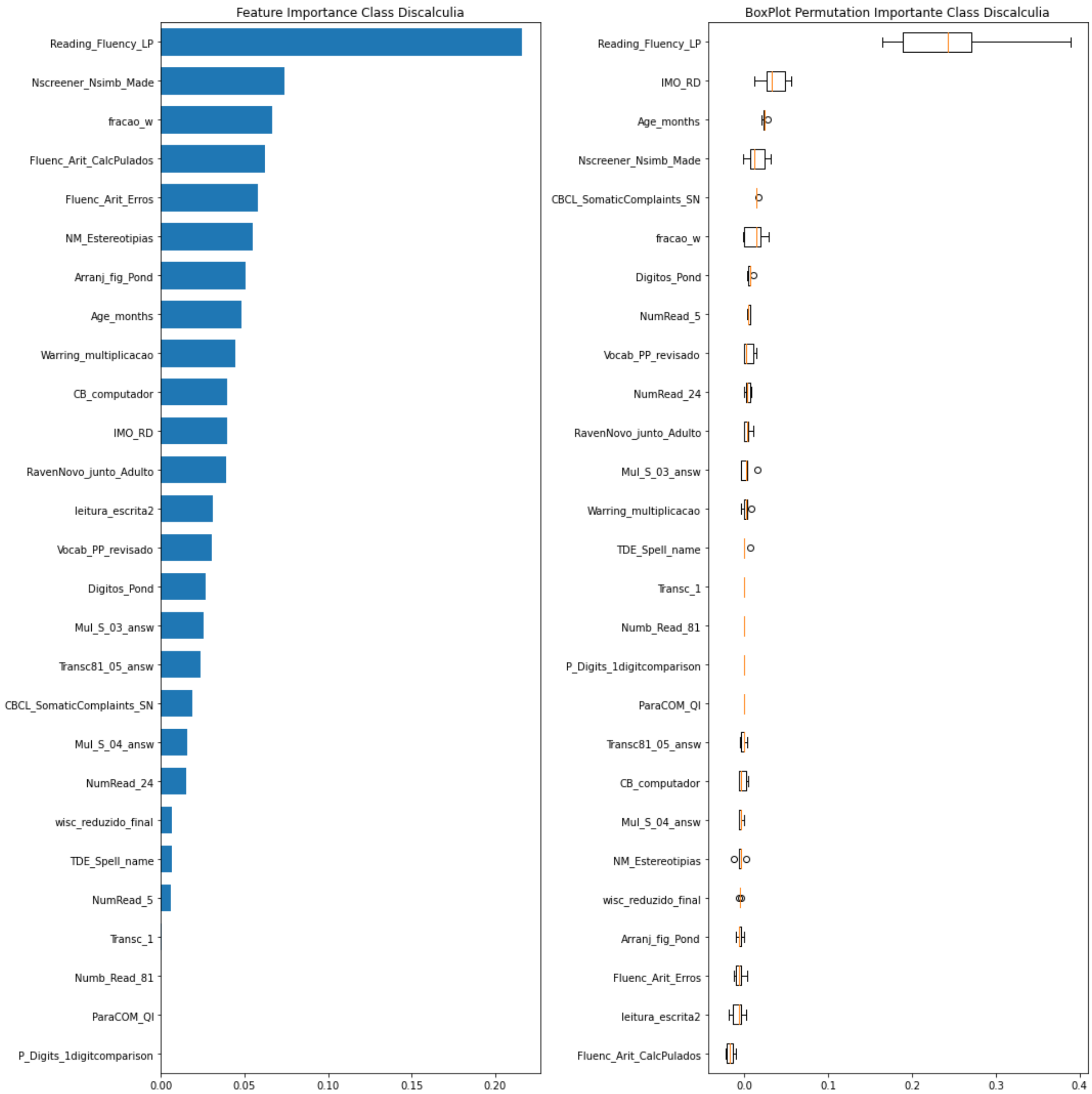


Figure 46 – Dataset083 : Variable Importance of Dyscalculia Class

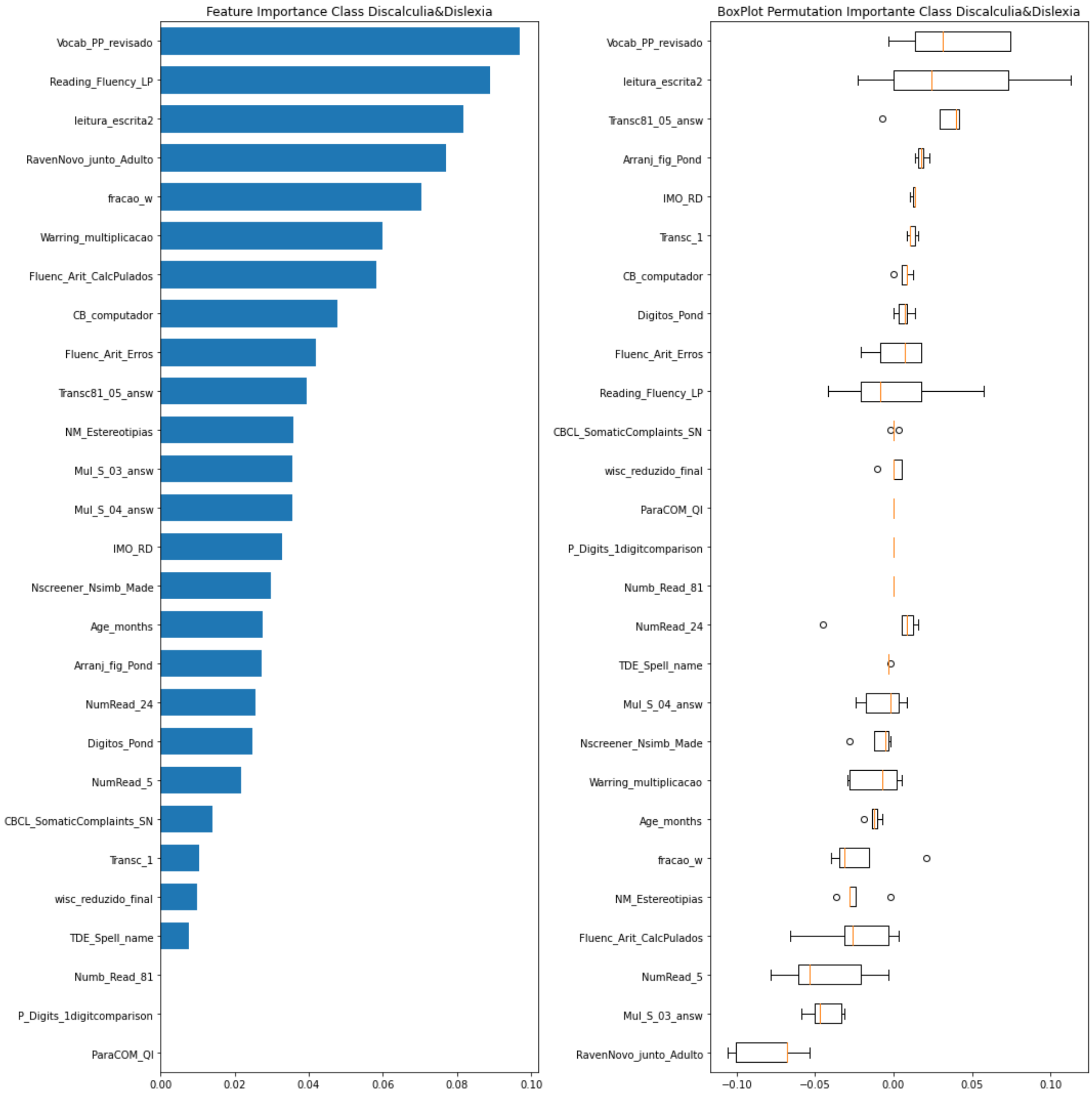


Figure 47 – Dataset083 : Variable Importance of Dyscalculia and Dyslexia Class

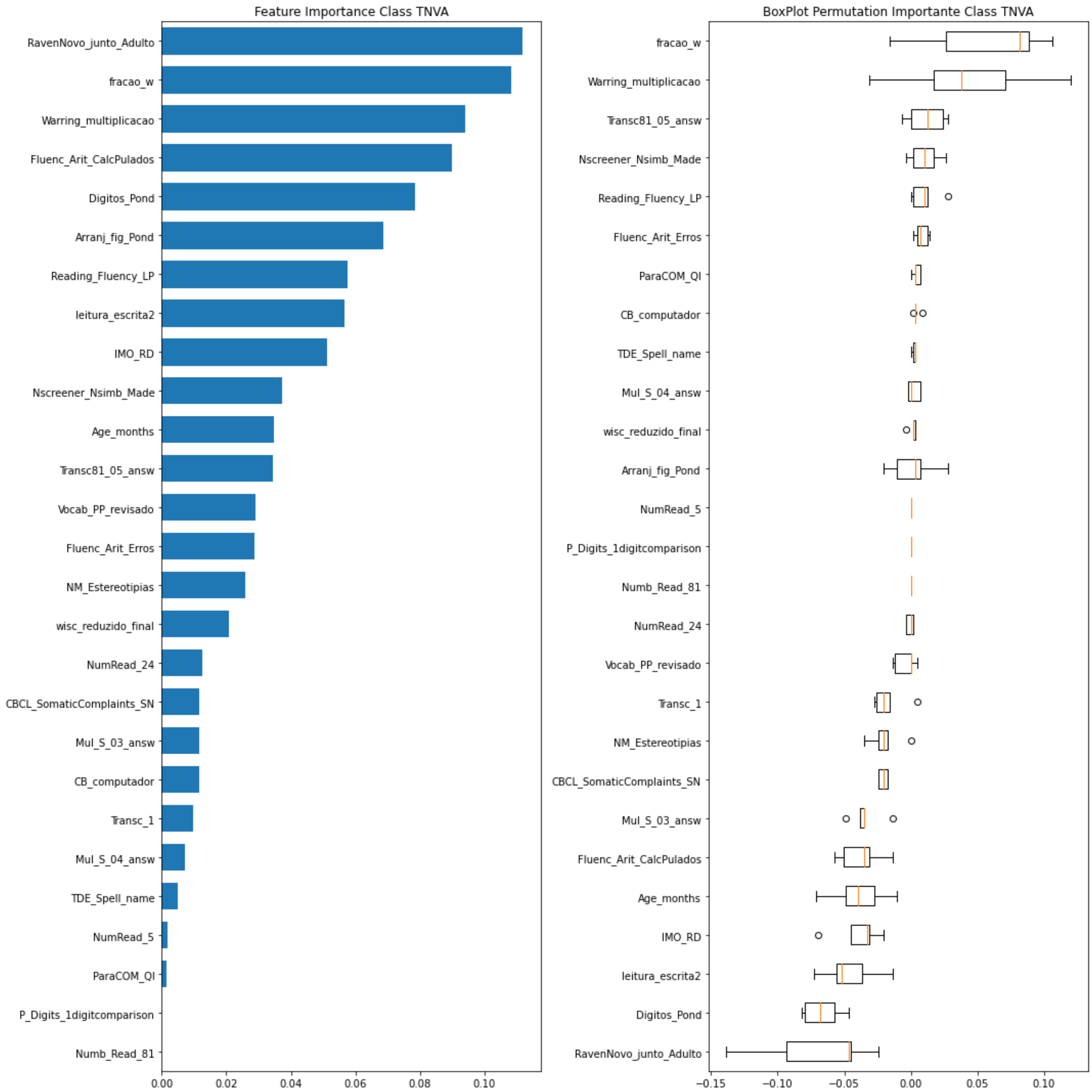


Figure 48 – Dataset083 : Variable Importance of NLD Class.

F.2 Dataset 149

The results of framework application over Dataset149 follow in the next sections.

F.2.1 BoxPlot

In this section we present box plots of framework application over Dataset149.

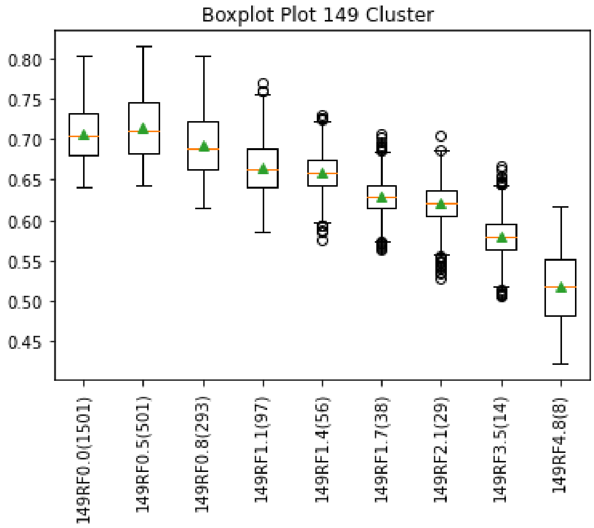


Figure 49 – Box Plot Dataset149 lap01

Threshold (n.variables)	Outliers (by 1000)
149RF0.0(1501)	0
149RF0.5(501)	0
149RF0.8(293)	0
149RF1.1(97)	0
149RF1.4(56)	8
149RF1.7(38)	10
149RF2.1(29)	8
149RF3.5(14)	5
149RF4.8(8)	0

Table 16 – Outliers Dataset149 lap01

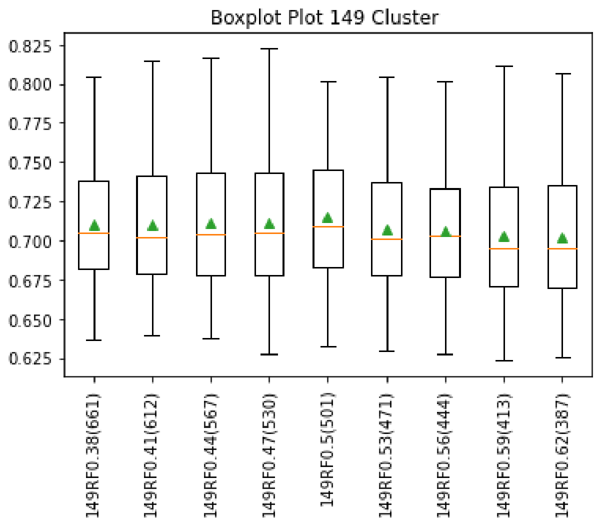


Figure 50 – Box Plot Dataset149 lap02

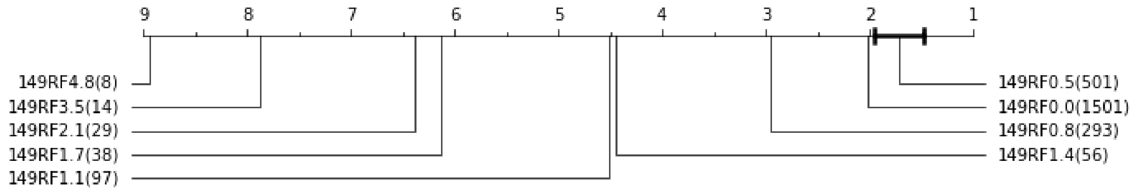
Threshold (n.variables)	Outliers (by 1000)
149RF0.38(661)	1
149RF0.41(612)	0
149RF0.44(567)	0
149RF0.47(530)	0
149RF0.5(501)	0
149RF0.53(471)	0
149RF0.56(444)	0
149RF0.59(413)	0
149RF0.62(387)	0

Table 17 – Outliers Dataset149 lap02

Outliers exhibit models' AUC metrics which are out of normal distribution. In all box plot graphics, the median's values appears as the box figure and the mean is represented as the red line. Outliers appears as small circles in the normal curve limits of graphic.

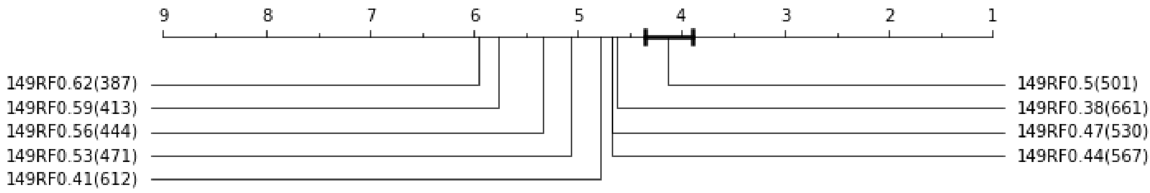
F.2.1.1 CD Graph

In this section we present CD graphs from framework application over Dataset149.



(a) CD graph based on Bonferroni-Dunn. Best average ranked is 149RF0.5, with no equivalence. At this first lap, as only one t is selected, another lap is executed considering that distance between threshold standard $t = 0.0$ and $t = 0.5$ is bigger than $\delta = 0.03$. The new inferior limit is 75% of the best, and 125% is the superior limit

.



(b) CD graph based on Bonferroni-Dunn. In this second lap, best average ranked is 149RF0.5 again, with no equivalence. At this time, as the distance between current best threshold $t = 0.5$ and the last best $t = 0.5$ is minor than $\delta = 0.03$, the process stops and the t referring model is selected.

F.2.2 ROC Curve

In this section we present ROC curve of framework application over Dataset149.

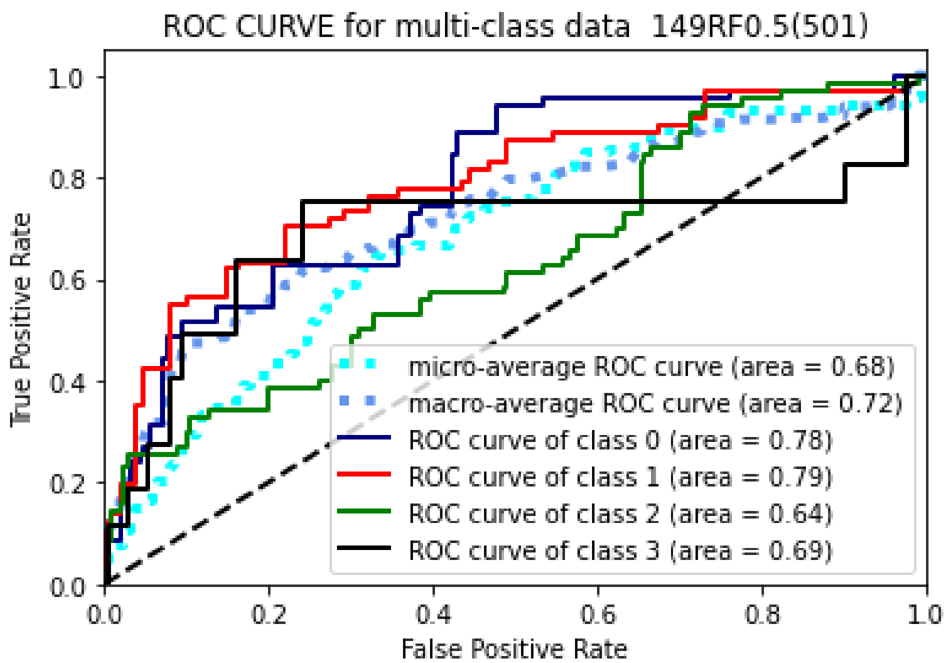


Figure 52 – Multiclass ROC Curve for best ranked RF classifier upon threshold cluster $t = 0.5$. With 501 leader variables, the model can perform the classification for diagnosis classes 0, 1 and 2, with macro averaged AUC of 72%. Performance for each class is shown at one-vs-rest curves.

F.2.3 Variable Importance Analyses

In this section we present the variable importance plots of framework application over Dataset149.

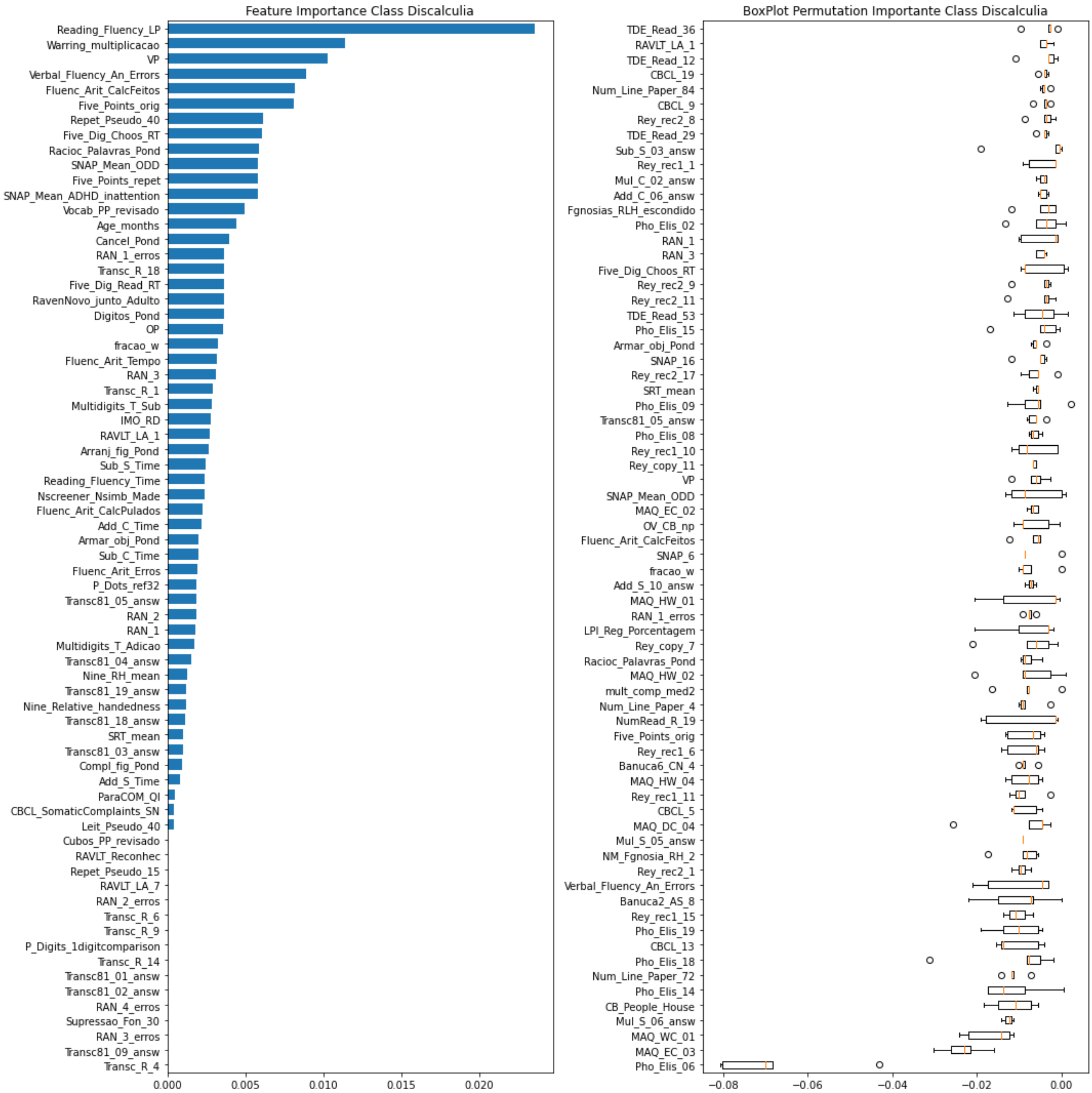


Figure 53 – Dataset149 : Variable Importance of Class Dyscalculia

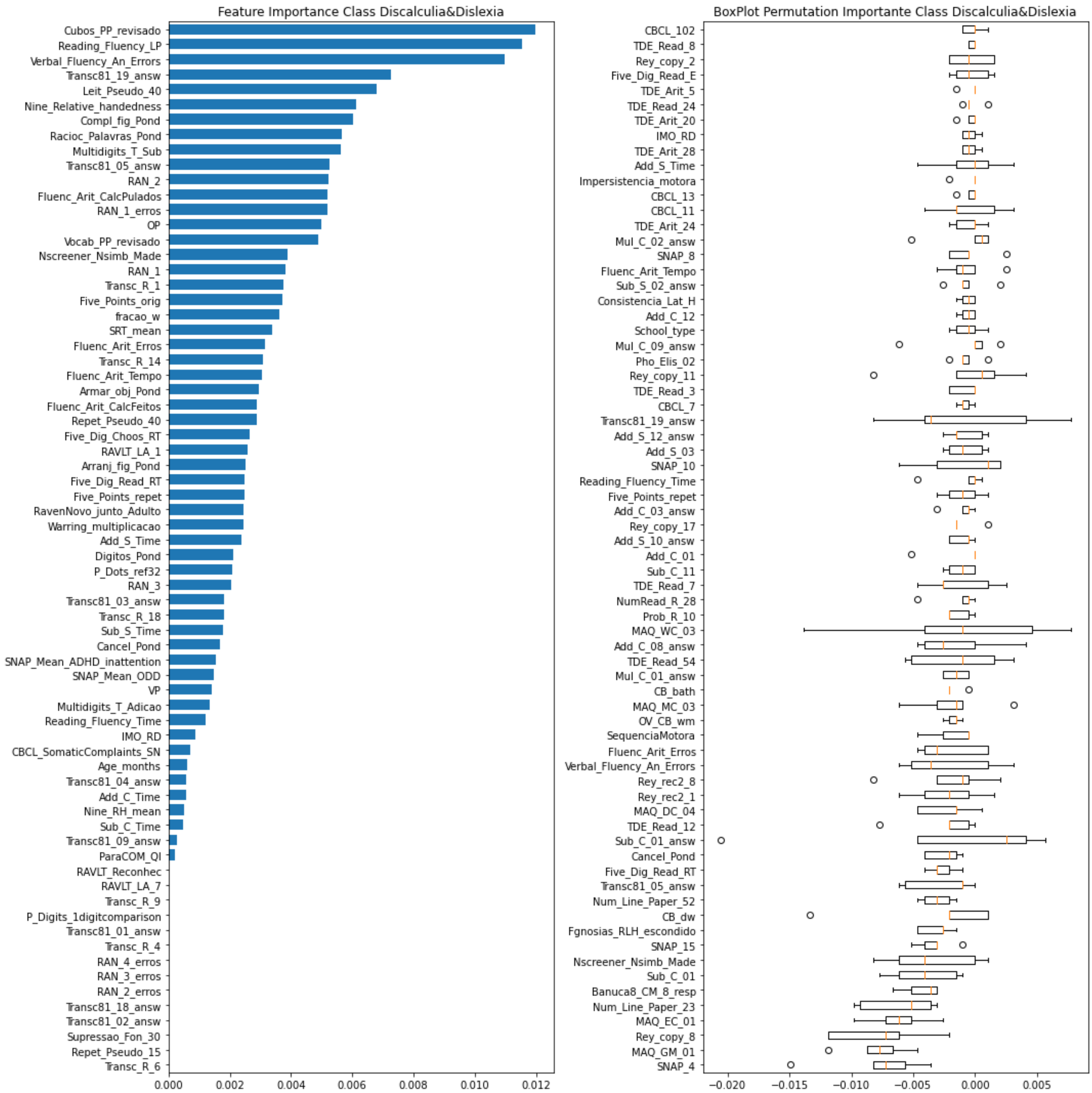


Figure 54 – Dataset149 : Variable Importance of Class Dyscalculia and Dyslexia.

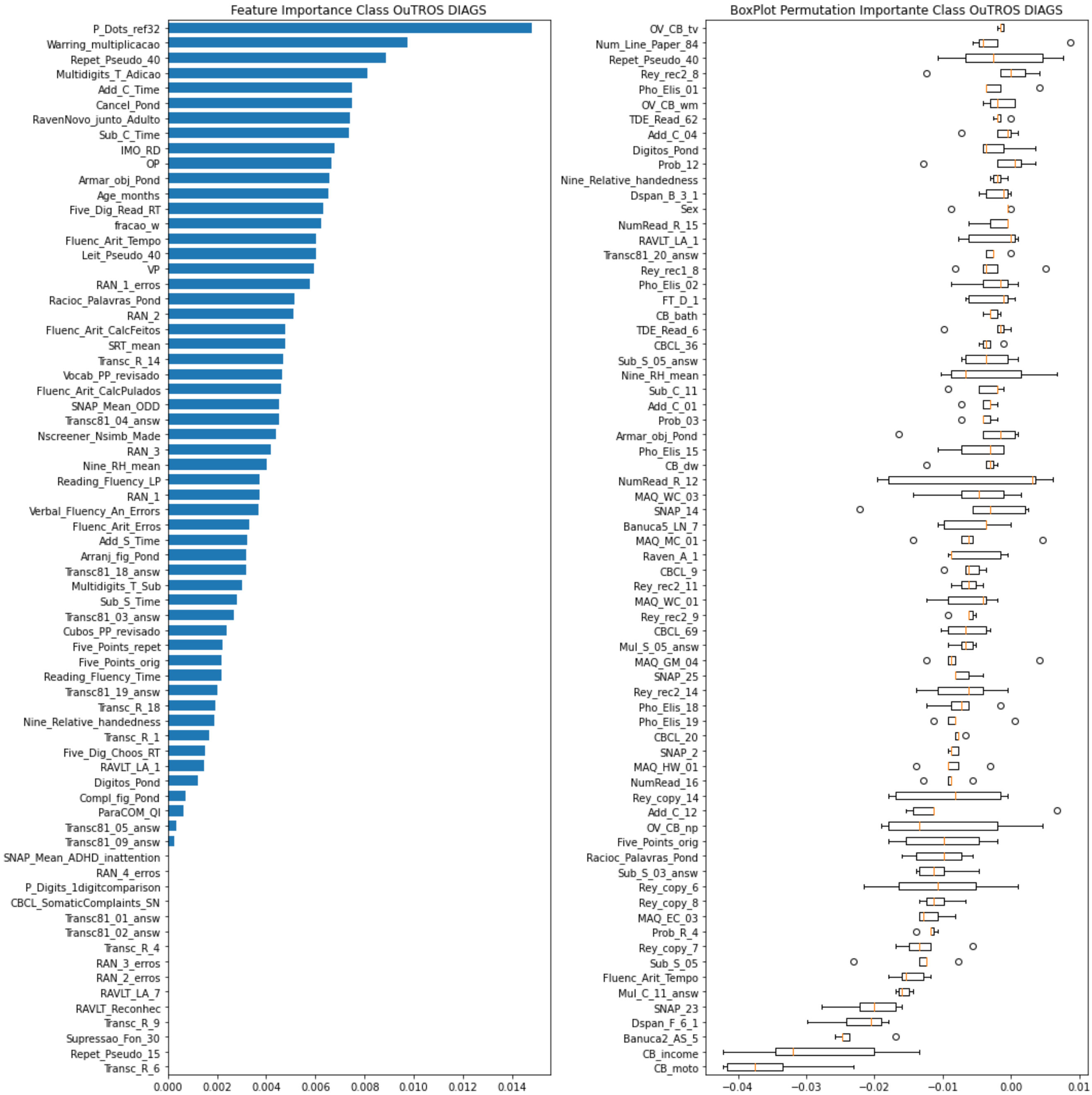


Figure 55 – Dataset149 :Variable Importance of Class Other Diagnoses

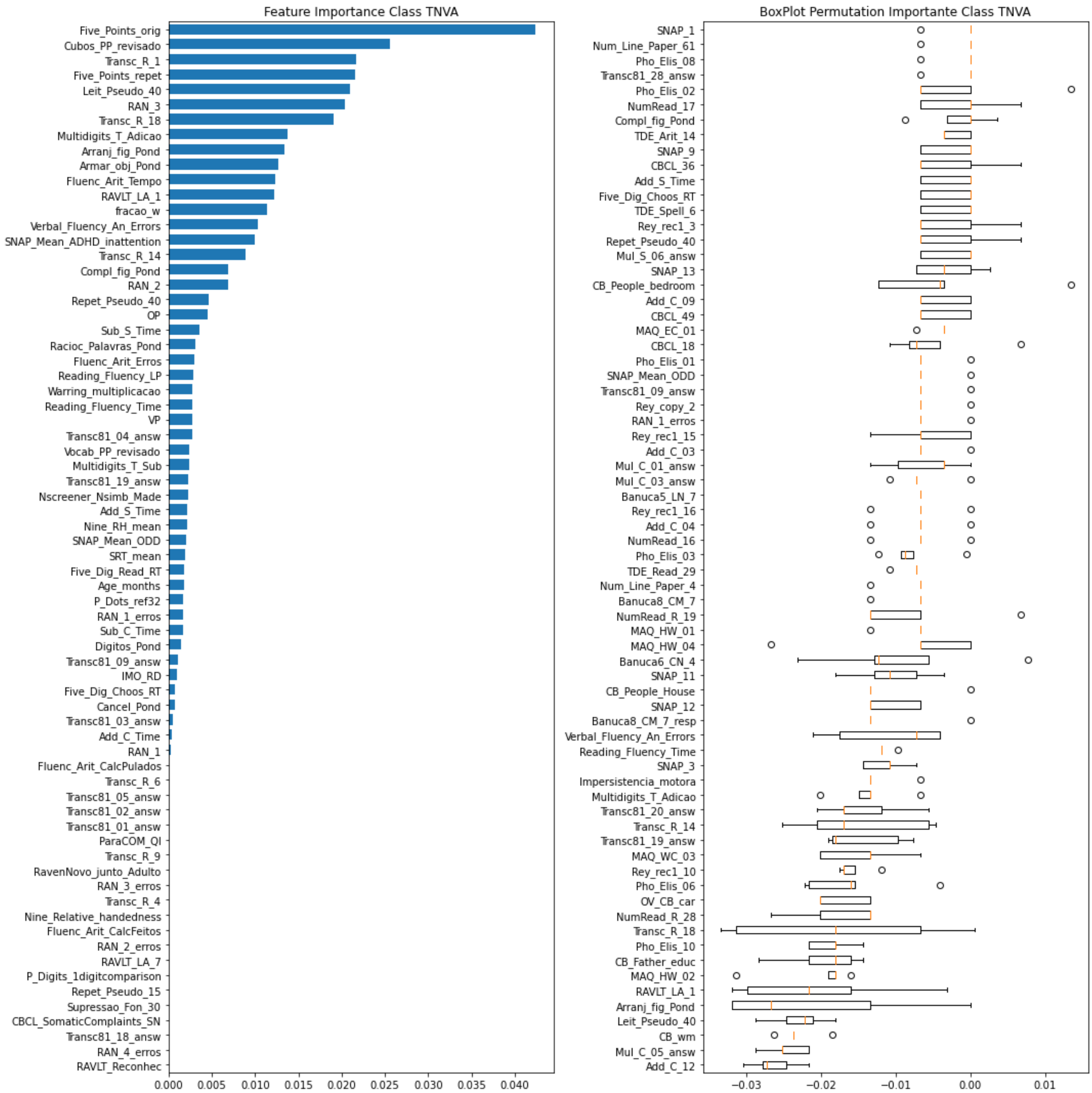


Figure 56 – Dataset149 : Variable Importance of Class NLD

F.3 Dataset 364

The results of framework application over Dataset364 follow in the next sections.

F.3.1 BoxPlot

In this section we present box plots plots of framework application over Dataset364.

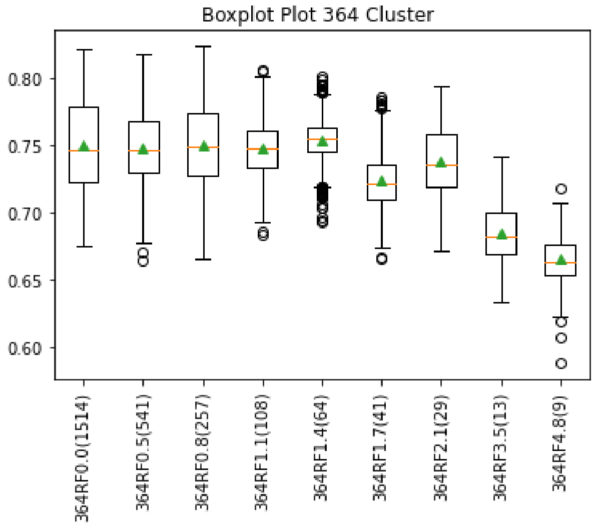


Figure 57 – Box Plot Dataset364 lap01

Threshold (n.variables)	Outliers (by 1000)
364RF0.0(1514)	0
364RF0.5(541)	0
364RF0.8(257)	0
364RF1.1(108)	1
364RF1.4(64)	18
364RF1.7(41)	2
364RF2.1(29)	0
364RF3.5(13)	1
364RF4.8(9)	2

Table 18 – Outliers Dataset364 lap01

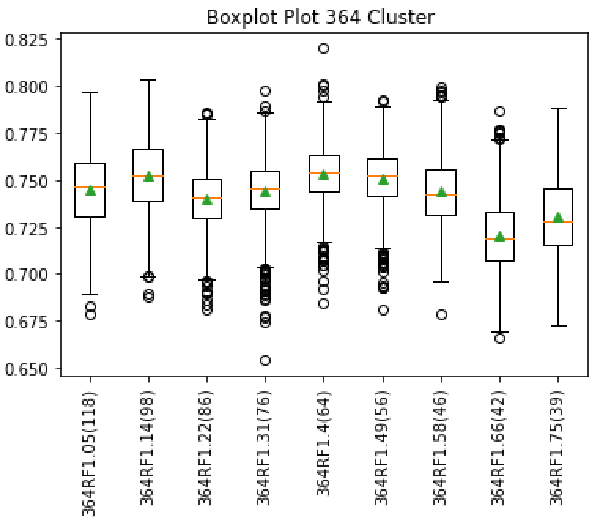


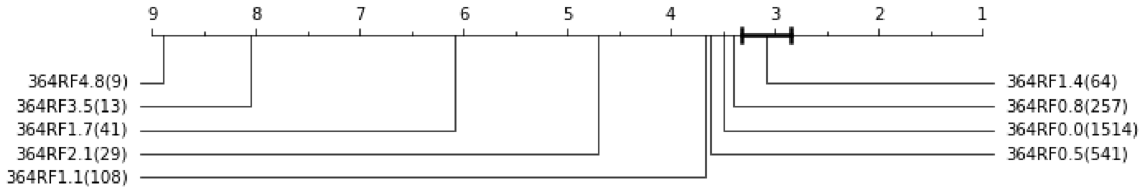
Figure 58 – Box Plot Dataset364 lap02

Threshold (n.variables)	Outliers (by 1000)
364RF1.05(118)	5
364RF1.14(98)	2
364RF1.22(86)	4
364RF1.31(76)	8
364RF1.4(64)	14
364RF1.49(56)	13
364RF1.58(46)	6
364RF1.66(42)	6
364RF1.75(39)	1

Table 19 – Outliers Dataset364 lap02

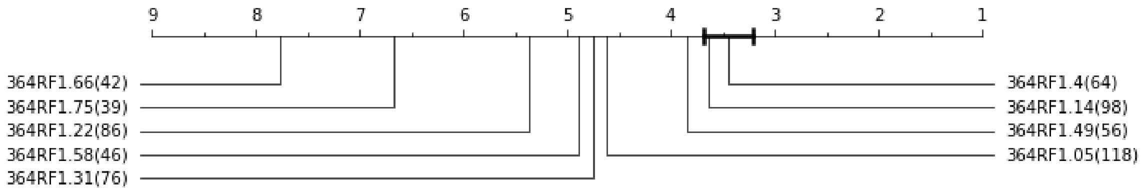
F.3.2 CD Graph

In this section we present CD graphs of framework application over Dataset364.



(a) CD graph based on Bonferroni-Dunn. Best average ranked is 364RF1.4, with no equivalence to any other classifier. At this first lap, when no equivalence is achieved between models, but the distance between threshold standard $t = 0.0$ and $t = 1.4$ is bigger than $\delta = 0.03$, another lap is executed considering the new inferior limit as 75% of the best, and 125% of best, as the superior limit

.



(b) CD graph based on Bonferroni-Dunn. In this second lap, best average ranked is 364RF1.4, with equivalence to 364RF1.14 classifier. At this lap, although the equivalence to another model, as the distance between last lap threshold $t = 1.4$ and the current $t = 1.4$ is less than $\delta = 0.03$, the process stops and selects $t = 1.4$

F.3.3 ROC Curve

In this section we present the ROC curve of framework application over Dataset364.

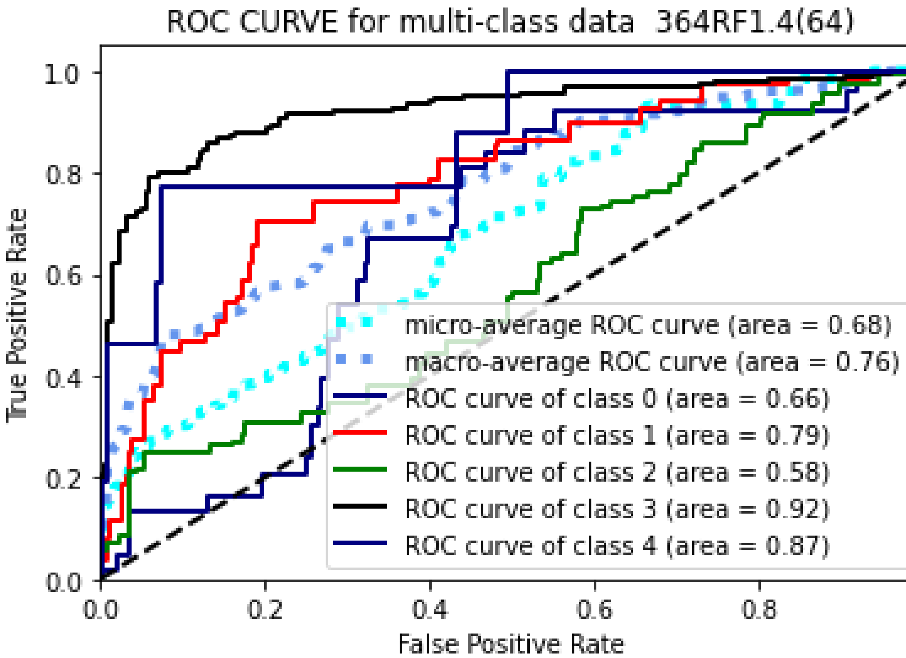


Figure 60 – Multiclass ROC Curve for best ranked RF classifier upon threshold cluster 1.4. With 64 leader variables, the model can perform the classification for diagnosis classes 0, 1 and 2. with macro average AUC of 76%. Performance for each class is shown at one-vs-rest curves.

F.3.4 Variable Importance Analyses

In this section we present the variable importance plots of framework application over Dataset364.

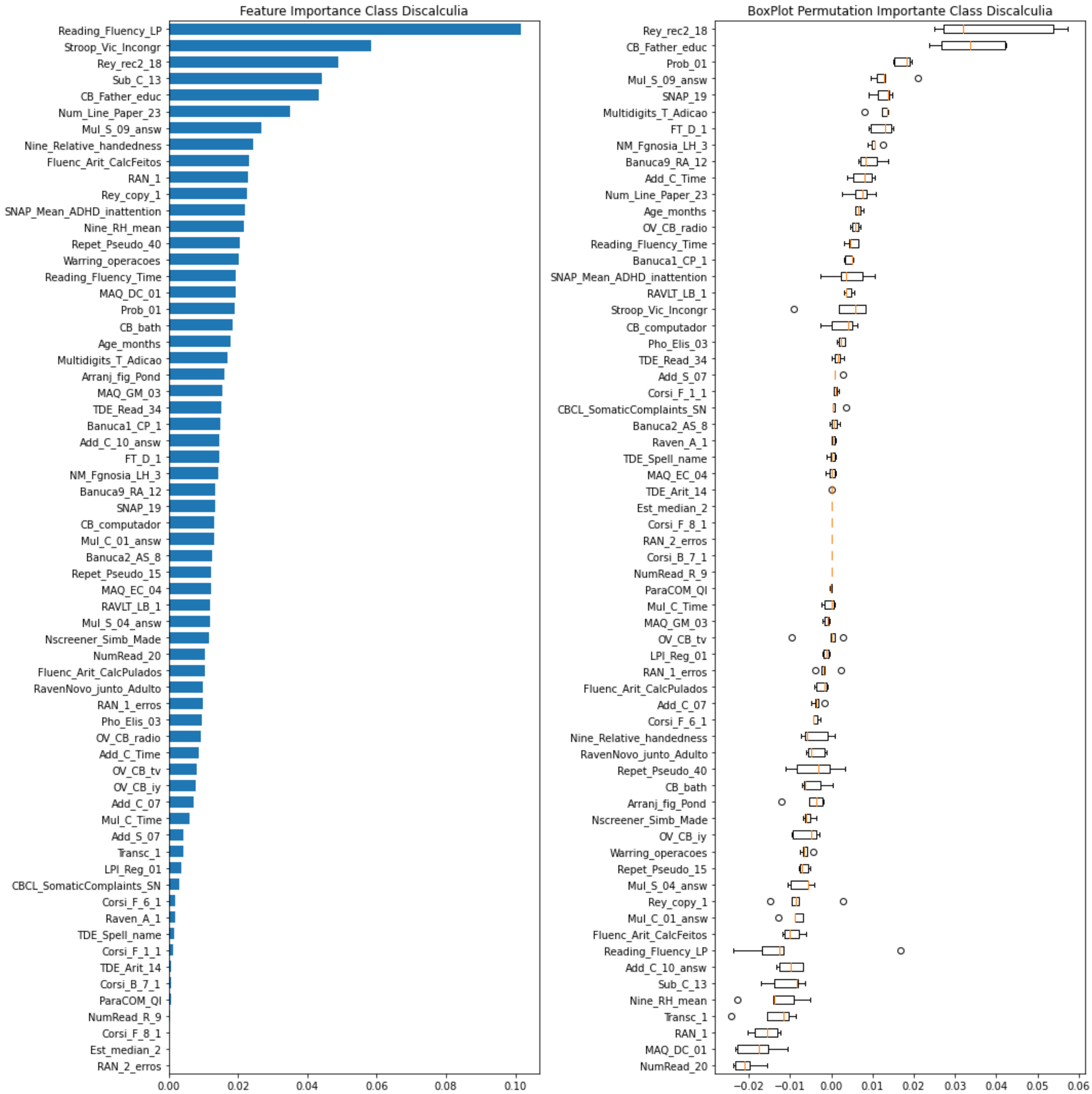


Figure 61 – Dataset364:Variable Importance of Class Dyscalculia

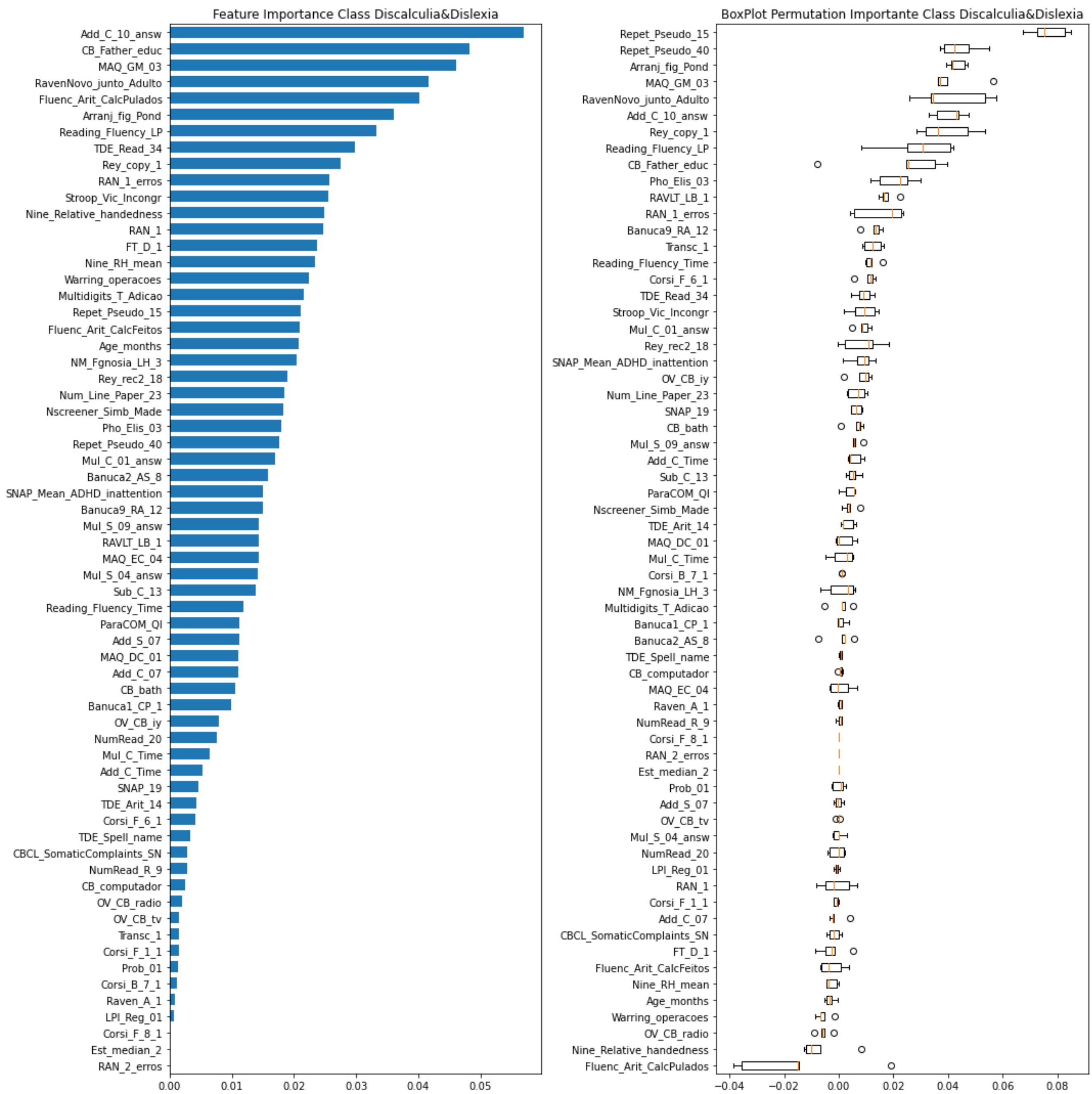


Figure 62 – Dataset364:Variable Importance of Class Dyscalculia and Dyslexia

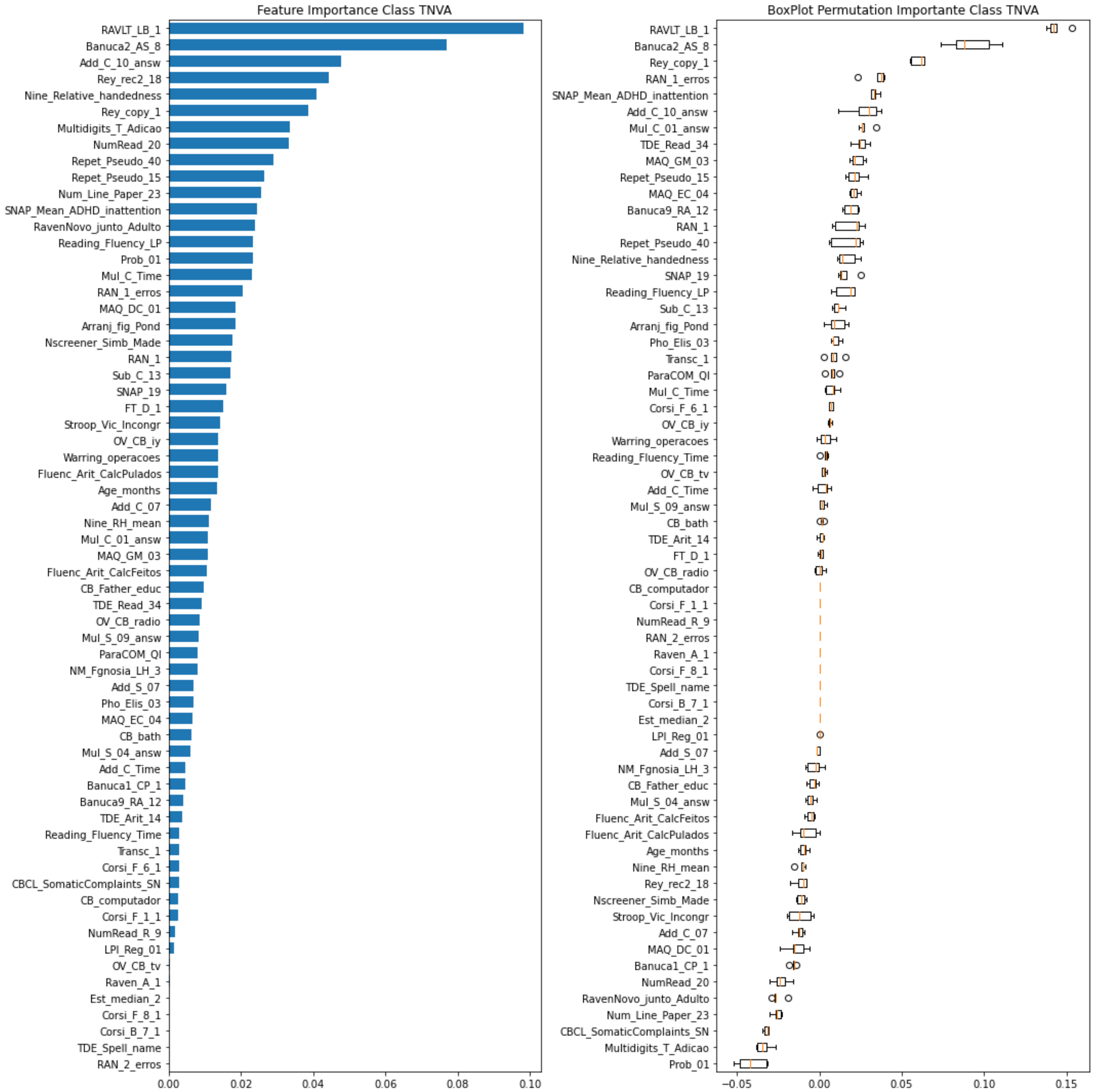


Figure 63 – Dataset364:Variable Importance of Class NLD

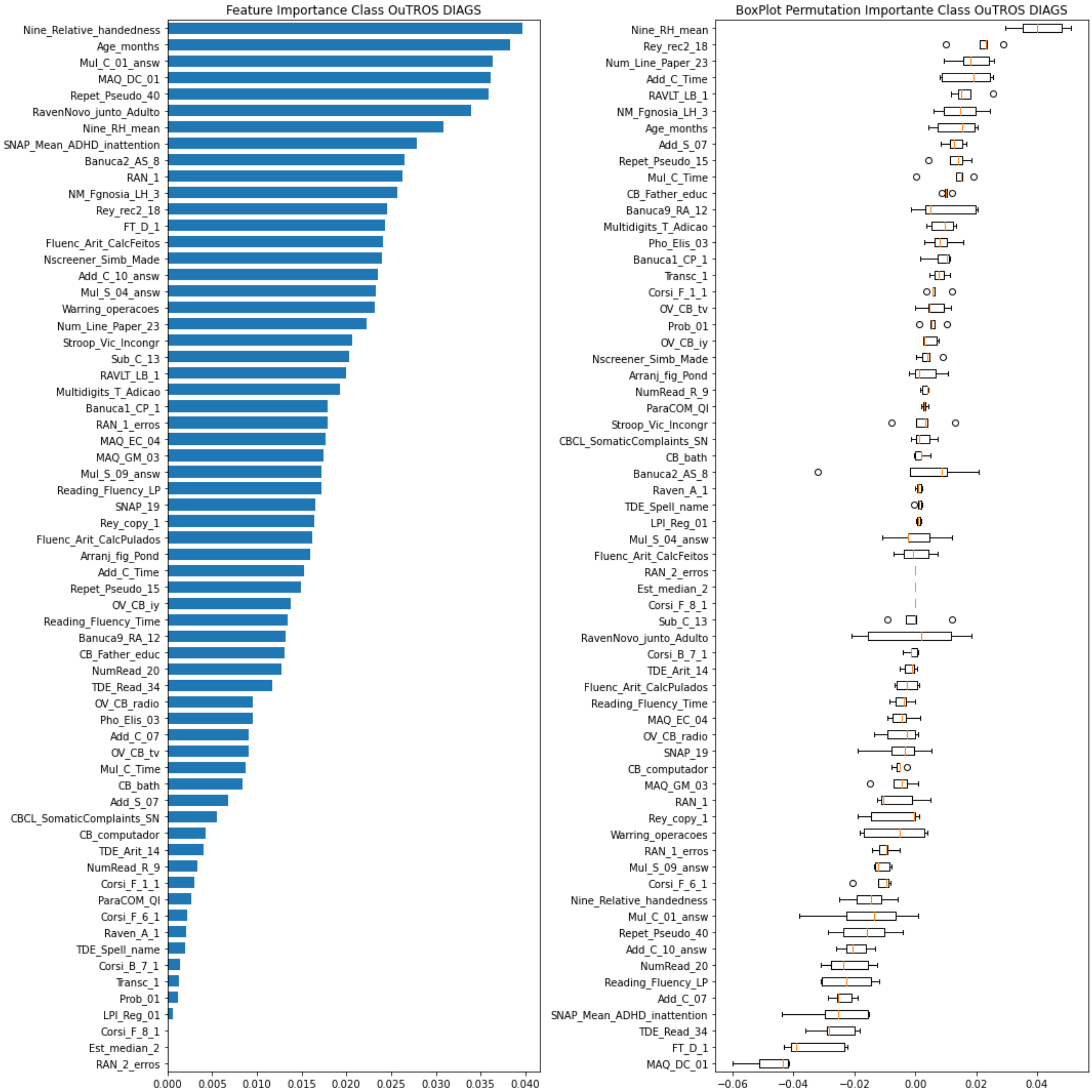


Figure 64 – Dataset364:Variable Importance of Class Other Diagnoses

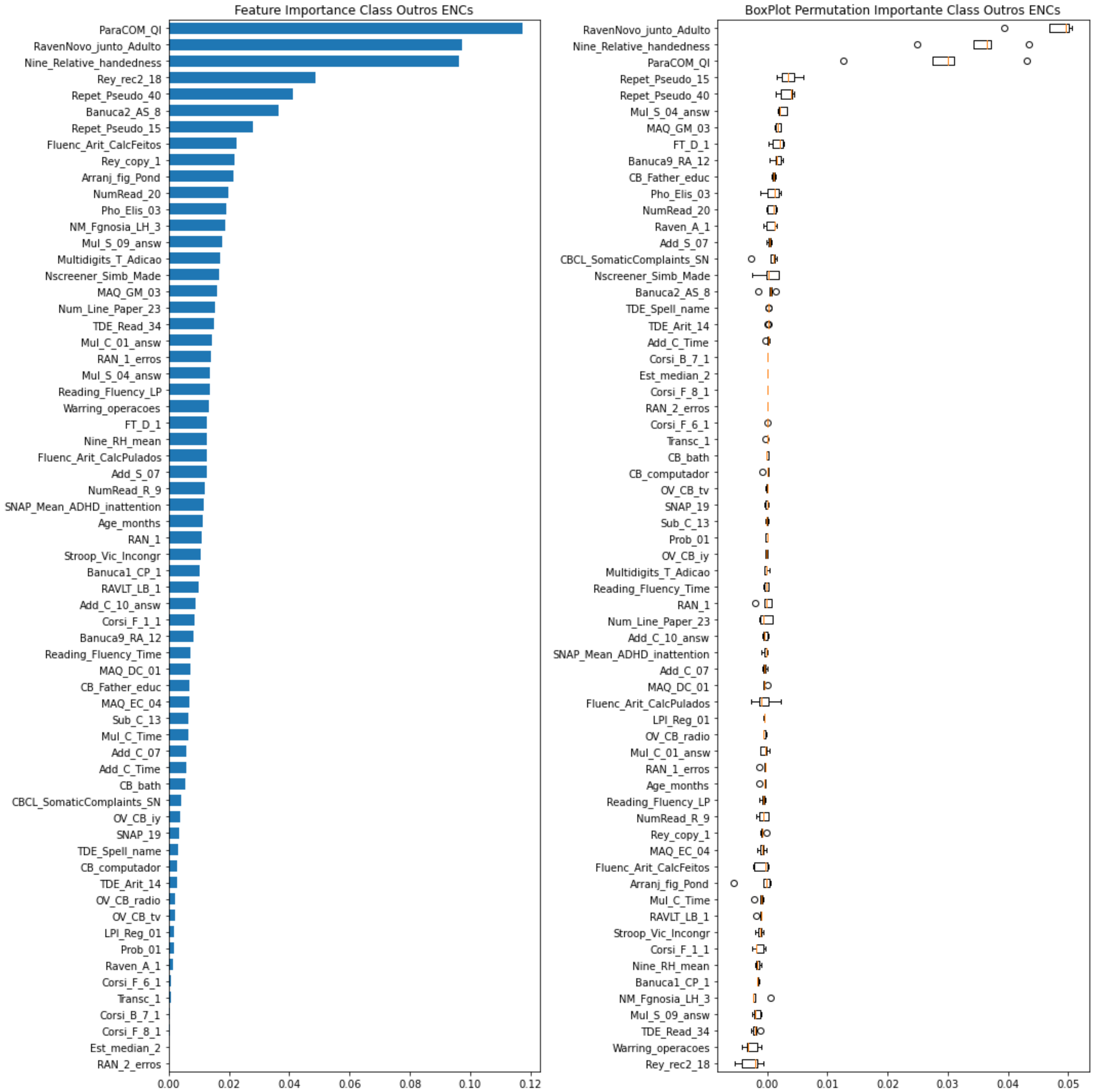


Figure 65 – Dataset364:Variable Importance of Class Outros Enc

G

Clusters threshold variables lists

In this appendice we present the chosen clusters composition, indicating for each leader variable, the complete list of variables within.

G.1 Dataset 083

Leader variables
0==>Age_months
3==>RavenNovo_junto_Adulto
5==>ParaCOM_QI
6==>Vocab_PP_revisado
11==>IMO_RD
16==>Digitos_Pond
21==>Arranj_fig_Pond
36==>fracao_w
38==>Fluenc_Arit_CalcPulados
40==>Fluenc_Arit_Erros
44==>Nscreener_Nsimb_Made
47==>Reading_Fluency_LP
55==>Numb_Read_81
59==>Warring_multiplicacao
72==>CBCL_SomaticComplaints_SN
81==>P_Digits_1digitcomparison
154==>Transc81_05_answ
235==>NumRead_5
254==>NumRead_24
396==>Mul_S_03_answ
397==>Mul_S_04_answ

449==>CB_computador
968==>NM_Estereotipias
978==>leitura_escrita2
1000==>wisc_reduzido_final
1057==>Transc_1
1352==>TDE_Spell_name

List of cluster variables

17==>[0, 1, 2, 49, 50, 51, 52, 53, 54, 105, 107, 364, 365, 366, 380, 381, 490, 506, 510, 512, 518, 721, 802, 807, 812, 817, 826, 834, 860, 963, 964, 966, 967, 971, 972, 973, 1012, 1013, 1014, 1015, 1024, 1025, 1026, 1027]
Variable Names ==> Age_months ,Age_years ,Grade ,Five_Dig_Read_RT ,Five_Dig_Cout_RT ,Five_Dig_Choos_RT ,Five_Dig_Switch_RT ,Five_Dig_Inhibit_RT ,Five_Dig_Flexib_RT ,SRT_sd ,SRT_max ,Sub_C_01 ,Sub_C_02 ,Sub_C_03 ,Sub_C_02_answ ,Sub_C_03_answ ,OV_CB_np ,MAQ_GM_04 ,MAQ_EC_04 ,MAQ_DC_02 ,MAQ_WC_04 ,Rey_rec2_1 ,Banuca6_CN_4 ,Banuca6_CN_9 ,Banuca6_CN_4_resp ,Banuca6_CN_9_resp ,Banuca7_RN_8, Banuca7_RN_8_resp ,Banuca9_RA_6 ,NM_Fgnosia_RH_2 , NM_Fgnosia_RH_3 ,NM_Fgnosia_LH_2 ,NM_Fgnosia_LH_3 , NM_Marcha_unip_D ,NM_Marcha_unip_E ,Consistencia_Lat_H , Corsi_F_6_1 , Corsi_F_6_2 ,Corsi_F_7_1 ,Corsi_F_7_2 , Corsi_B_5_1 ,Corsi_B_5_2 ,Corsi_B_6_1 ,Corsi_B_6_2

27==>[3, 4, 7, 10, 14, 24, 31, 32, 33, 34, 484, 487, 495, 538, 564, 565, 566, 567, 568, 569, 570, 571, 572, 574, 576, 577, 578, 579, 580, 704, 706, 707, 715, 716, 720, 722, 738]
Variable Names ==> RavenNovo_junto_Adulto ,Inteligencia_FINAL_juntos ,Cubos_PP_revisado ,OP ,QI_E ,Conc_Fig_Pond ,Nine_RH_mean ,Nine_DH_mean ,Nine_LH_mean ,Nine_NDH_mean ,OV_CB_hm ,OV_CB_ref ,OV_CB_hm_score ,Pho_Elis_09 ,Rey_copy_2 ,Rey_copy_3 ,Rey_copy_4 ,Rey_copy_5 ,Rey_copy_6 ,Rey_copy_7 ,Rey_copy_8 ,Rey_copy_9 ,Rey_copy_10 ,Rey_copy_12 ,Rey_copy_14 ,Rey_copy_15 ,Rey_copy_16 ,Rey_copy_17 ,Rey_copy_18 ,Rey_rec1_2 ,Rey_rec1_4 ,Rey_rec1_5 ,Rey_rec1_13 ,Rey_rec1_14 ,Rey_rec1_18 ,Rey_rec2_2 ,Rey_rec2_18 ,

25==>[5, 35, 82, 83, 84, 85, 271, 272, 273, 274, 275, 276, 277, 279, 280, 281, 283, 284, 304, 353, 379, 383, 395, 409, 429, 430, 437, 441, 442, 455, 462, 463, 474, 480, 481, 488, 491, 492, 499, 509, 517, 534, 537, 559, 563, 713, 731, 734, 975, 976, 1001, 1040, 1041, 1042, 1043, 1206, 1207, 1208, 1209, 1210, 1211, 1212, 1213, 1214, 1215, 1216, 1217, 1218, 1219, 1220, 1221, 1222, 1223, 1224, 1225, 1226, 1227, 1228, 1229, 1231, 1542, 1545]
Variable Names ==> ParaCOM_QI ,Nine_Relative_handedness ,SNAP_Mean_ADHD_inattention ,SNAP_Mean_ADHD_hyperactivity , SNAP_Mean_ADHD_combined ,SNAP_Mean_ODD ,NumRead_R_13 ,NumRead_R_14

,NumRead_R_15 ,NumRead_R_17 ,NumRead_R_18 ,NumRead_R_19 ,NumRead_R_20 ,NumRead_R_22 ,NumRead_R_23 ,NumRead_R_24 ,NumRead_R_26 ,NumRead_R_27 ,Add_S_07_answ ,Sub_S_02_answ ,Sub_C_01_answ ,Sub_C_05_answ ,Mul_S_02_answ ,Mul_C_01_answ ,Prob_08 ,Prob_09 ,Prob_R_4 ,Prob_R_8 ,Prob_R_9 ,CB_mcw ,CB_People_House ,CB_People_bedroom ,CB_mw_score ,OV_CB_tv ,OV_CB_radio ,OV_CB_freezer ,OV_CB_tv_score ,OV_CB_radio_score ,OV_CB_freezer_score , MAQ_EC_03 ,MAQ_WC_03 ,Pho_Elis_05 ,Pho_Elis_08 ,Five_Dig_Count_E ,Rey_copy_1 ,Rey_rec1_11 ,Rey_rec2_11 ,Rey_rec2_14 ,SES_juntado ,SES_justado_nominal ,preferencia_manual ,Dspan_F_6_1 ,Dspan_F_6_2 ,Dspan_F_7_1 ,Dspan_F_7_2 ,SNAP_1 ,SNAP_2 ,SNAP_3 ,SNAP_4 ,SNAP_5 ,SNAP_6 ,SNAP_7 ,SNAP_8 ,SNAP_9 ,SNAP_10 ,SNAP_11 ,SNAP_12 ,SNAP_13 ,SNAP_14 ,SNAP_15 ,SNAP_16 ,SNAP_17 ,SNAP_18 ,SNAP_19 ,SNAP_20 ,SNAP_21 ,SNAP_22 ,SNAP_23 ,SNAP_24 ,SNAP_26 ,Oponencia ,Impersistencia_motora ,

20==>[6, 8, 9, 12, 13, 15, 17, 18, 19, 20, 22, 28, 29, 56, 57, 58, 66, 104, 106, 418, 421, 447, 453, 454, 457, 461, 466, 472, 473, 476, 507, 708, 717, 718, 723, 726, 729, 732, 735, 736, 929, 969, 970, 999]
Variable Names ==> Vocab_PP_revisado ,QI_T ,CV ,VP ,QI_V ,Semel_PP_Triagem ,Semelh_Pond ,Inform_Pond ,Compreen_Pon ,Compl_fig_Pond ,Armar_obj_Pond ,Codigos_Pond ,Proc_Simb_Pond ,Multidigits_T_Adicao ,Multidigits_T_Sub ,Multidigits_T_Mult ,RAN_3 ,SRT_mean ,SRT_min ,Mul_C_10_answ ,Mul_C_13_answ ,CB_maid ,CB_wm ,CB_dvd ,CB_drm ,CB_Mother_educ ,CB_maid_score ,CB_wm_score ,CB_dvd_score ,CB_drm_score ,MAQ_EC_01 ,Rey_rec1_6 ,Rey_rec1_15 ,Rey_rec1_16 ,Rey_rec2_3 ,Rey_rec2_6 ,Rey_rec2_9 ,Rey_rec2_12 ,Rey_rec2_15 ,Rey_rec2_16 ,mult_comp_med2 ,NM_index_nose_eyes_open ,NM_index_nose_eyes_close ,School_type ,

26==>[11, 23, 26, 46, 354, 358, 446, 450, 451, 452, 464, 465, 469, 470, 471, 486, 497, 508, 519, 522, 524, 525, 526, 573, 575, 703, 705, 719, 733, 895, 897, 901, 902, 909, 917, 946, 1028, 1029, 1050, 1051, 1052, 1053, 1054, 1055, 1532]
Variable Names ==> IMO_RD ,Racioc_Matric_Pon ,Seq_N_Let_Pon ,Reading_Fluency_Time ,Sub_S_03_answ ,
Sub_S_07_answ ,CB_bath ,CB_dw ,CB_fridge ,CB_freezer ,CB_income ,CB_bath_score ,CB_dw_score ,CB_fridge_score ,CB_freezer_score ,OV_CB_dvd ,OV_CB_dvd_score ,MAQ_EC_02 ,MAQ_MC_01 ,MAQ_MC_04 ,MAQ_HW_02 ,MAQ_HW_03 ,MAQ_HW_04 ,Rey_copy_11 ,Rey_copy_13 ,Rey_rec1_1 ,Rey_rec1_3 ,Rey_rec1_17 ,Rey_rec2_13 ,Num_Line_Paper_79 ,Num_Line_Paper_84 ,Num_Line_Paper_81 ,Num_Line_Paper_90 ,Num_Line_Paper_96 ,Num_Line_Paper_72 ,mult_comp_acc1 ,Corsi_B_7_1 ,Corsi_B_7_2 ,Dspan_B_4_1 ,Dspan_B_4_2 ,Dspan_B_5_1 ,Dspan_B_5_2 ,Dspan_B_6_1 ,Dspan_B_6_2 ,NM_Pantonima1 ,

9==>[16, 75, 76, 78, 79, 80, 282, 286, 298, 310, 325, 355, 399, 711, 712, 1002, 1003, 1004, 1005, 1006, 1007, 1008, 1009, 1010, 1011, 1016, 1017, 1018, 1019, 1020, 1021, 1022, 1023, 1030, 1031, 1032, 1033, 1034, 1035, 1036, 1037, 1038, 1039, 1044, 1045, 1046, 1047, 1048, 1049]
Variable Names ==> Digitos_Pond ,Add_C_Time ,Sub_S_Time ,Mul_S_Time ,Mul_C_Time ,P_Dots_ref32 ,NumRead_R_25 ,Add_S_01 ,Add_S_01_answ ,Add_C_01 ,Add_C_01_answ ,Sub_S_04_answ ,Mul_S_06_answ ,Rey_rec1_9 ,Rey_rec1_10 ,Corsi_F_1_1 ,Corsi_F_1_2 ,Corsi_F_2_1 ,Corsi_F_2_2 ,Corsi_F_3_1 ,Corsi_F_3_2 ,Corsi_F_4_1 ,Corsi_F_4_2 ,Corsi_F_5_1 ,Corsi_F_5_2 ,Corsi_B_1_1 ,Corsi_B_1_2 ,Corsi_B_2_1 ,Corsi_B_2_2 ,Corsi_B_3_1 ,Corsi_B_3_2 ,Corsi_B_4_1 ,Corsi_B_4_2 ,Dspan_F_1_1 ,Dspan_F_1_2 ,Dspan_F_2_1 ,Dspan_F_2_2 ,Dspan_F_3_1 ,Dspan_F_3_2 ,Dspan_F_4_1 ,Dspan_F_4_2 ,Dspan_F_5_1 ,Dspan_F_5_2 ,Dspan_B_1_1 ,Dspan_B_1_2 ,Dspan_B_2_1 ,Dspan_B_2_2 ,Dspan_B_3_1 ,Dspan_B_3_2 ,

13==>[21, 25, 27, 30, 37, 41, 42, 43, 63, 68, 74, 86, 90, 100, 101, 102, 103, 109, 316, 317, 318, 319, 320, 321, 322, 323, 324, 331, 332, 333, 335, 336, 337, 338, 339, 348, 349, 350, 351, 360, 361, 362, 363, 368, 369, 370, 371, 372, 373, 374, 375, 376, 377, 378, 385, 386, 387, 398, 400, 401, 402, 403, 405, 407, 410, 411, 412, 415, 501, 527, 528, 666, 727, 728, 772, 780, 805, 815, 838, 840, 841, 842, 848, 849, 851, 856, 857, 858, 865, 866, 867, 868, 869, 873, 880, 881, 883, 884, 885, 886, 887, 888, 889, 890, 928, 931, 932, 936, 938, 941, 945]
Variable Names ==> Arranj_fig_Pond ,Arit_Pond ,Racioc_Palavras_Pond ,Cancel_Pond ,Fluenc_Arit_CalcFeitos ,Fluenc_Arit_Corretas ,Nscreener_Simb_Made ,Nscreener_Simb_TC ,Repet_Pseudo_40 ,RAN_1_erros ,Add_S_Time ,Verbal_Fluency_An_Corrects ,Five_Points_erros ,Stroop_Vic_Color ,Stroop_Vic_ColorW ,Stroop_Vic_Incongr ,Stroop_Vic_Interf ,Verbal_Fluency_An_Repetition ,Add_C_07 ,Add_C_08 ,Add_C_09 ,Add_C_10 ,Add_C_11 ,Add_C_12 ,Add_C_13 ,Add_C_14 ,Add_C_15 ,Add_C_07_answ ,Add_C_08_answ ,Add_C_09_answ ,Add_C_11_answ ,Add_C_12_answ ,Add_C_13_answ ,Add_C_14_answ ,Add_C_15_answ ,Sub_S_09 ,Sub_S_10 ,Sub_S_11 ,Sub_S_12 ,Sub_S_09_answ ,Sub_S_10_answ ,Sub_S_11_answ ,Sub_S_12_answ ,Sub_C_05 ,Sub_C_06 ,Sub_C_07 ,Sub_C_08 ,Sub_C_09 ,Sub_C_10 ,Sub_C_11 ,Sub_C_12 ,Sub_C_13 ,Sub_C_14 ,Sub_C_15 ,Sub_C_07_answ ,Sub_C_08_answ ,Sub_C_09_answ ,Mul_S_05_answ ,Mul_S_07_answ ,Mul_S_08_answ ,Mul_S_09_answ ,Mul_S_10_answ ,Mul_S_12_answ ,Mul_S_14_answ ,Mul_C_02_answ ,Mul_C_03_answ ,Mul_C_04_answ ,Mul_C_07_answ ,OV_Mother_ed_level ,LPI_Reg_Porcentagem ,LPI_Irreg_Porcentagem ,TDE_Read_70 ,Rey_rec2_7 ,Rey_rec2_8 ,Banuca4_SS_6 ,Banuca4_SS_6_resp ,Banuca6_CN_7 , Banuca6_CN_7_resp ,Banuca8_CM_4 ,Banuca8_CM_6 ,Banuca8_CM_7 ,Banuca8_CM_8 ,Banuca8_CM_4_resp ,Banuca8_CM_5_resp ,Banuca8_CM_7_resp ,Banuca9_RA_2 ,Banuca9_RA_3 ,Banuca9_RA_4 ,Banuca9_RA_11 ,Banuca9_RA_12 ,Banuca9_RA_13 ,Banuca9_RA_14 ,Banuca9_RA_15 ,Banuca9_RA_4_resp ,Banuca9_RA_11_resp ,Banuca9_RA_12_resp ,Banuca9_RA_14_resp ,Banuca9_RA_15_resp ,Fgnosia_RH_visivel

,Fgnosia_RH_escondido ,Fgnosia_RH_dois_dedos ,Fgnosia_LH_visivel ,Fgnosia_LH_escondido ,Fgnosia_LH_dois_dedos ,mult_comp_med1 ,mult_comp_med4 ,mult_comp_med5 , mult_comp_med9 ,mult_comp_dp2 ,mult_comp_dp5 ,mult_comp_dp9 ,

1==>[36, 39, 515, 558, 609, 714, 1425, 1426, 1427, 1428, 1429, 1430, 1431, 1432, 1433, 1434, 1435, 1436, 1437, 1438, 1439, 1440, 1441, 1442, 1443, 1444, 1445, 1446, 1447, 1448, 1449, 1450, 1451, 1452, 1453, 1454, 1455, 1456, 1457, 1458, 1459, 1460, 1461, 1462, 1463, 1464, 1465, 1466, 1467, 1468, 1469, 1470, 1471, 1472, 1473, 1474, 1475, 1476, 1477, 1478, 1479, 1480, 1481, 1482, 1483, 1484]
Variable Names ==> fracao_w ,Fluenc_Arit_Tempo ,MAQ_WC_01 ,Five_Dig_Read_E ,TDE_Read_13 ,Rey_rec1_12 ,LPI_Reg_01 ,LPI_Reg_02 ,LPI_Reg_03 ,LPI_Reg_04 ,LPI_Reg_05 ,LPI_Reg_06 ,LPI_Reg_07 ,LPI_Reg_08 ,LPI_Reg_09 ,LPI_Reg_10 ,LPI_Reg_11 ,LPI_Reg_12 ,LPI_Reg_13 ,LPI_Reg_14 ,LPI_Reg_15 ,LPI_Reg_16 ,LPI_Reg_17 ,LPI_Reg_18 ,LPI_Reg_19 ,LPI_Reg_20 ,LPI_Irreg_01 ,LPI_Irreg_02 ,LPI_Irreg_03 ,LPI_Irreg_04 ,LPI_Irreg_05 ,LPI_Irreg_06 ,LPI_Irreg_07 ,LPI_Irreg_08 ,LPI_Irreg_09 ,LPI_Irreg_10 ,LPI_Irreg_11 ,LPI_Irreg_12 ,LPI_Irreg_13 ,LPI_Irreg_14 ,LPI_Irreg_15 ,LPI_Irreg_16 ,LPI_Irreg_17 ,LPI_Irreg_18 ,LPI_Irreg_19 ,LPI_Irreg_20 ,LPI_Pseud_01 ,LPI_Pseud_02 ,LPI_Pseud_03 ,LPI_Pseud_04 ,LPI_Pseud_05 ,LPI_Pseud_06 ,LPI_Pseud_07
LPI_Pseud_08 ,LPI_Pseud_09 ,LPI_Pseud_10 ,LPI_Pseud_11 ,LPI_Pseud_12 ,LPI_Pseud_13 ,LPI_Pseud_14 ,LPI_Pseud_15 ,LPI_Pseud_16 ,LPI_Pseud_17 ,LPI_Pseud_18 ,LPI_Pseud_19 ,LPI_Pseud_20 ,

7==>[38, 285, 287, 288, 289, 290, 291, 292, 293, 294, 295, 296, 297, 300, 303, 305, 306, 308, 309, 311, 312, 313, 314, 315, 326, 327, 329, 340, 341, 342, 343, 344, 345, 346, 347, 357, 359, 422, 423, 424, 425, 426, 427, 428, 431, 432, 433, 434, 435, 436, 438, 439, 440, 443, 444, 445, 605, 710, 977]
Variable Names ==> Fluenc_Arit_CalcPulados ,NumRead_R_28 ,Add_S_02 ,Add_S_03 ,Add_S_04 ,Add_S_05 ,Add_S_06 ,Add_S_07 ,Add_S_08 ,Add_S_09 ,Add_S_10 ,Add_S_11 ,Add_S_12 ,Add_S_03_answ ,
Add_S_06_answ , Add_S_08_answ ,Add_S_09_answ ,Add_S_11_answ ,Add_S_12_answ , Add_C_02,Add_C_03 ,Add_C_04 ,Add_C_05 ,Add_C_06 ,
Add_C_02_answ ,Add_C_03_answ ,Add_C_05_answ ,Sub_S_01 ,Sub_S_02 ,Sub_S_03 ,Sub_S_04 ,Sub_S_05 ,Sub_S_06 ,Sub_S_07 ,Sub_S_08 ,Sub_S_06_answ ,Sub_S_08_answ ,Prob_01 ,Prob_02 ,Prob_03 ,Prob_04 ,Prob_05 ,Prob_06 ,Prob_07 ,Prob_10 ,Prob_11 ,Prob_12 ,Prob_R_1 ,Prob_R_2 ,Prob_R_3 ,Prob_R_5 ,Prob_R_6 ,Prob_R_7 ,Prob_R_10 ,Prob_R_11 ,Prob_R_12 ,TDE_Read_9 ,Rey_rec1_8 ,Sex ,

5==>[40, 328, 416, 503, 523, 598, 599, 600, 601, 602, 603, 604, 606, 607, 608, 611, 612, 613, 614, 615, 616, 617, 618, 619, 620, 621, 622, 623, 624, 625, 626, 627, 628, 629, 633, 634, 635, 637, 638, 639, 641, 642, 643, 645, 646, 647, 648, 653, 655, 657, 659, 660]

Variable Names ==> Fluenc_Arit_Erros ,Add_C_04_answ ,Mul_C_08_answ ,MAQ_GM_01 ,MAQ_HW_01 ,TDE_Read_2 ,TDE_Read_3 ,TDE_Read_4 ,TDE_Read_5 ,TDE_Read_6 ,TDE_Read_7 ,TDE_Read_8 ,TDE_Read_10 ,TDE_Read_11 ,TDE_Read_12 ,TDE_Read_15 ,TDE_Read_16 ,TDE_Read_17 ,TDE_Read_18 ,TDE_Read_19 , TDE_Read_20 ,TDE_Read_21 ,TDE_Read_22 ,TDE_Read_23 ,TDE_Read_24 ,TDE_Read_25 ,TDE_Read_26 ,TDE_Read_27 ,TDE_Read_28 ,TDE_Read_29 ,TDE_Read_30 ,TDE_Read_31 ,TDE_Read_32 ,TDE_Read_33 ,TDE_Read_37 ,TDE_Read_38 ,TDE_Read_39 ,TDE_Read_41 ,TDE_Read_42 ,TDE_Read_43 ,TDE_Read_45 ,TDE_Read_46 ,TDE_Read_47 ,TDE_Read_49 ,TDE_Read_50 ,TDE_Read_51 ,TDE_Read_52 ,TDE_Read_57 ,TDE_Read_59 ,TDE_Read_61 ,TDE_Read_63 ,TDE_Read_64 ,

15==>[44, 45, 48, 108, 334, 388, 389, 390, 391, 392, 393, 394, 456, 475, 482, 493, 505, 511, 513, 514, 520, 521, 747, 755, 763, 764, 765, 766, 771, 773, 779, 781, 789, 797, 803, 806, 808, 813, 816, 818, 835, 843, 850, 859, 864, 874, 875, 879, 898, 899, 918, 919, 937, 947, 948, 949, 950, 951, 952, 953, 954]
Variable Names ==> Nscreener_Nsimb_Made ,Nscreener_Nsimb_TC ,Reading_Fluency_Errors ,wrsquared ,Add_C_10_answ ,Sub_C_10_answ ,Sub_C_11_answ ,Sub_C_12_answ ,Sub_C_13_answ ,Sub_C_14_answ ,Sub_C_15_answ ,Mul_S_01_answ ,CB_moto ,CB_moto_score ,OV_CB_bath ,OV_CB_bath_score ,MAQ_GM_03 ,MAQ_DC_01 ,MAQ_DC_03 ,MAQ_DC_04 ,MAQ_MC_02 ,MAQ_MC_03 ,Banuca2_AS_3 ,Banuca2_AS_3_resp ,Banuca3_C_3 ,Banuca3_C_4 ,Banuca3_C_5 ,Banuca3_C_6 ,Banuca4_SS_5 ,Banuca4_SS_7 ,Banuca4_SS_5_resp ,Banuca4_SS_7_resp ,Banuca5_LN_7 ,Banuca5_LN_7_resp ,Banuca6_CN_5 ,Banuca6_CN_8 ,Banuca6_CN_10 ,Banuca6_CN_5_resp ,Banuca6_CN_8_resp ,Banuca6_CN_10_resp ,Banuca8_CM_1 ,Banuca8_CM_9 ,Banuca8_CM_6_resp ,Banuca9_RA_5 ,Banuca9_RA_10 ,Banuca9_RA_5_resp ,Banuca9_RA_6_resp ,Banuca9_RA_10_resp ,Num_Line_Paper_61 ,Num_Line_Paper_64 ,Num_Line_Paper_Ajust_Linear ,Num_Line_Paper_Aju ,mult_comp_dp1 ,mult_comp_acc2 ,mult_comp_acc3 ,mult_comp_acc4 ,mult_comp_acc5 ,mult_comp_acc6 ,mult_comp_acc7 ,mult_comp_acc8 ,mult_comp_acc9 ,

19==>[47, 62, 64, 65, 67, 87, 89, 91, 92, 93, 94, 95, 96, 97, 117, 119, 122, 123, 124, 125, 126, 127, 129, 130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142, 143, 144, 145, 146, 147, 148, 149, 367, 382, 413, 419, 496, 516, 529, 762, 836, 846, 930, 933, 934, 935, 939, 942, 943, 944, 956, 957, 958, 959, 960, 961]
Variable Names ==>
Reading_Fluency_LP ,Leit_Pseudo_40 ,RAN_1 ,RAN_2 ,RAN_4 , Verbal_Fluency_An_Errors ,Five_Points_repet ,RAVLT_LA_1 ,RAVLT_LA_2 ,RAVLT_LA_3 ,RAVLT_LA_4 ,RAVLT_LA_5 ,RAVLT_LB_1 ,RAVLT_LA_6 ,Transc_R_8 ,Transc_R_10 ,Transc_R_13 ,Transc_R_14 ,Transc_R_15 ,Transc_R_16 ,Transc_R_17 ,Transc_R_18 ,Transc_R_20 ,Transc_R_21 ,Transc_R_22 ,Transc_R_23 ,Transc_R_24 ,Transc_R_25 ,Transc_R_26 ,Transc_R_27 ,Transc_R_28 ,Transc_R_29 ,Transc_R_30 ,Transc_R_31 ,Transc_R_32

,Transc_R_33 ,Transc_R_34 ,Transc_R_35 ,Transc_R_36 ,Transc_R_37 ,Transc_R_38 ,Transc_R_39 ,Transc_R_40 ,Sub_C_04 ,Sub_C_04_answ ,Mul_C_05_answ ,Mul_C_11_answ ,OV_CB_wm_score ,MAQ_WC_02 ,LPI_Pseud_Porcentagem ,Banuca3_C_2 ,Banuca8_CM_2 ,Banuca8_CM_2_resp ,mult_comp_med3 ,mult_comp_med6 ,mult_comp_med7 ,mult_comp_med8 ,mult_comp_dp3 ,mult_comp_dp6 ,mult_comp_dp7 ,mult_comp_dp8 ,FT_D_1 ,FT_D_2 ,FT_RH_mean_final ,FT_E_1 ,FT_E_2 ,FT_LH_mean_final

21==>[55, 69, 70, 71, 77, 98, 99, 110, 111, 112, 113, 114, 115, 116, 118, 120, 121, 128, 150, 151, 157, 158, 231, 232, 233, 234, 237, 238, 239, 241, 259, 260, 261, 262, 265, 266, 267, 269, 404, 408, 458, 477, 498, 581, 582, 583, 584, 585, 586, 587, 588, 589, 594, 597, 610, 667, 668, 669, 670, 671, 672, 673, 677, 678, 679, 680, 681, 682, 683, 684, 685, 686, 687, 688, 689, 690, 691, 692, 693, 694, 695, 696, 697, 698, 699, 700, 701, 702, 730, 739, 740, 741, 742, 743, 744, 745, 746, 748, 749, 750, 751, 752, 753, 754, 756, 757, 758, 759, 760, 761, 767, 768, 769, 770, 775, 776, 777, 778, 783, 784, 785, 786, 787, 788, 790, 791, 792, 793, 794, 795, 796, 798, 799, 800, 801, 804, 809, 810, 811, 814, 819, 820, 821, 822, 823, 824, 825, 827, 828, 829, 830, 831, 832, 833, 844, 845, 855, 861, 862, 870, 876, 891, 920, 921, 922, 923, 924, 925, 926, 927, 962, 965]
Variable Names ==> Numb_Read_81 ,RAN_2_erros ,RAN_3_erros ,RAN_4_erros ,Sub_C_Time ,RAVLT_LA_7 ,RAVLT_Reconhec ,Transc_R_1 ,Transc_R_2 ,Transc_R_3 ,Transc_R_4 ,Transc_R_5 ,Transc_R_6 ,Transc_R_7 ,Transc_R_9 ,Transc_R_11 ,Transc_R_12 ,Transc_R_19 ,Transc81_01_answ ,Transc81_02_answ ,Transc81_08_answ ,Transc81_09_answ ,NumRead_1 ,NumRead_2 ,NumRead_3 ,NumRead_4 ,NumRead_7 ,NumRead_8 ,NumRead_9 ,NumRead_11 ,NumRead_R_1 ,NumRead_R_2 ,NumRead_R_3 ,NumRead_R_4 ,NumRead_R_7 ,NumRead_R_8 ,NumRead_R_9 ,NumRead_R_11 ,Mul_S_11_answ ,Mul_S_15_answ ,CB_water ,CB_water_score ,OV_CB_ref_score ,Digits_error_1 ,Digits_error_2 ,Digits_error_3 ,Digits_error_4 ,Digits_error_6 ,Digits_error_7 ,Digits_error_8 ,Digits_error_9 ,Digits_arcsine_1 ,Digits_arcsine_7 ,TDE_Read_1 ,TDE_Read_14 ,Orient_1 ,Orient_2 ,Orient_3 ,Orient_4 ,Orient_5 ,Orient_6 ,Orient_7 ,Orient_11 ,Orient_12 ,Fgnosia_RH_1 ,Fgnosia_RH_2 ,Fgnosia_RH_3 ,Fgnosia_RH_4 ,Fgnosia_RH_5 ,Fgnosia_RH_6 ,Fgnosia_RH_7 ,Fgnosia_RH_8 ,Fgnosia_RH_9 ,Fgnosia_RH_10 ,Fgnosia_RH_11 ,Fgnosia_RH_12 ,Fgnosia_LH_1 ,Fgnosia_LH_2 ,Fgnosia_LH_3 ,Fgnosia_LH_4 ,Fgnosia_LH_5 ,Fgnosia_LH_6 ,Fgnosia_LH_7 ,Fgnosia_LH_8 ,Fgnosia_LH_9 ,Fgnosia_LH_10 ,Fgnosia_LH_11 ,Fgnosia_LH_12 ,Rey_rec2_10 , Banuca1_CP_1 ,Banuca1_CP_2 ,Banuca1_CP_3 ,Banuca1_CP_4 ,Banuca1_CP_5 ,Banuca1_CP_6 ,Banuca2_AS_1 ,Banuca2_AS_2 ,Banuca2_AS_4 ,Banuca2_AS_5 ,Banuca2_AS_6 ,Banuca2_AS_7 ,Banuca2_AS_8 ,Banuca2_AS_1_resp ,Banuca2_AS_2_resp ,Banuca2_AS_4_resp ,Banuca2_AS_5_resp ,Banuca2_AS_6_resp ,Banuca2_AS_7_resp ,Banuca2_AS_8_resp ,Banuca3_C_1 ,Banuca4_SS_1 ,
Banuca4_SS_2 ,Banuca4_SS_3 ,Banuca4_SS_4 ,Banuca4_SS_1_resp ,Banuca4_SS_2_resp

,Banuca4_SS_3_resp ,Banuca4_SS_4_resp ,Banuca5_LN_1 ,Banuca5_LN_2 ,Banuca5_LN_3 ,Banuca5_LN_4 ,Banuca5_LN_5 ,Banuca5_LN_6 ,Banuca5_LN_8 ,Banuca5_LN_1_resp ,Banuca5_LN_2_resp ,Banuca5_LN_3_resp ,Banuca5_LN_4_resp ,Banuca5_LN_5_resp ,Banuca5_LN_6_resp ,Banuca5_LN_8_resp ,Banuca6_CN_1 ,Banuca6_CN_2 ,Banuca6_CN_3 ,Banuca6_CN_6 ,Banuca6_CN_1_resp ,Banuca6_CN_2_resp ,Banuca6_CN_3_resp ,Banuca6_CN_6_resp ,Banuca7_RN_1 ,Banuca7_RN_2 ,Banuca7_RN_3 ,Banuca7_RN_4 ,Banuca7_RN_5 ,Banuca7_RN_6 ,Banuca7_RN_7 ,Banuca7_RN_1_resp ,Banuca7_RN_2_resp ,Banuca7_RN_3_resp ,Banuca7_RN_4_resp ,Banuca7_RN_5_resp ,Banuca7_RN_6_resp ,Banuca7_RN_7_resp ,Banuca8_CM_10 ,Banuca8_CM_1_resp ,Banuca9_RA_1 ,Banuca9_RA_7 ,Banuca9_RA_8 ,Banuca9_RA_1_resp ,Banuca9_RA_7_resp ,Fgnosias_RLH_visivel ,Span_PP_1 ,Span_PP_2 ,Span_PP_3 ,Span_PP_4 ,Span_PP_5 ,Span_PP_6 ,Span_PP_7 ,Span_PP_8 ,NM_Fgnosia_RH_1 ,NM_Fgnosia_LH_1 ,

2==>[59, 60, 61, 88, 152, 153, 155, 156, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169, 170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 180, 181, 182, 183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194, 195, 196, 197, 198, 199, 200, 201, 202, 203, 204, 205, 206, 207, 208, 209, 210, 211, 212, 213, 214, 215, 216, 217, 218, 219, 220, 221, 222, 223, 224, 225, 226, 227, 228, 229, 230, 384, 417, 420, 459, 478, 504, 709, 853, 854, 955, 1097, 1098, 1099, 1100, 1101, 1102, 1103, 1104, 1105, 1106, 1107, 1108, 1109, 1110, 1111, 1112, 1113, 1114, 1115, 1116, 1117, 1118, 1119, 1120, 1121, 1122, 1123, 1124, 1125, 1126, 1127, 1128, 1129, 1130, 1131, 1132, 1133, 1134, 1135, 1136, 1137, 1138, 1139, 1140, 1141, 1142, 1143, 1144, 1145, 1146, 1147, 1148, 1149, 1150, 1151, 1152, 1153, 1154, 1155, 1156, 1157, 1158, 1159, 1160, 1161, 1162, 1163, 1164, 1165, 1166, 1167, 1168, 1169, 1170, 1171, 1172, 1173, 1174, 1175, 1176, 1177]
Variable Names ==> Warring_multiplicacao ,Warring_operacoes ,Warring_cotidiano ,Five_Points_orig ,Transc81_03_answ ,Transc81_04_answ ,Transc81_06_answ ,Transc81_07_answ ,Transc81_10_answ ,Transc81_11_answ ,Transc81_12_answ ,Transc81_13_answ ,Transc81_14_answ ,Transc81_15_answ ,Transc81_16_answ ,Transc81_17_answ ,Transc81_18_answ ,Transc81_19_answ ,Transc81_20_answ ,Transc81_21_answ ,Transc81_22_answ ,Transc81_23_answ ,Transc81_24_answ ,Transc81_25_answ ,Transc81_26_answ ,Transc81_27_answ ,Transc81_28_answ ,Transc81_29_answ ,Transc81_30_answ ,Transc81_31_answ ,Transc81_32_answ ,Transc81_33_answ ,Transc81_34_answ ,Transc81_35_answ ,Transc81_36_answ ,Transc81_37_answ ,Transc81_38_answ ,Transc81_39_answ ,Transc81_40_answ ,Transc81_41_answ ,Transc81_42_answ ,Transc81_43_answ ,Transc81_44_answ ,Transc81_45_answ ,Transc81_46_answ ,Transc81_47_answ ,Transc81_48_answ ,Transc81_49_answ ,Transc81_50_answ ,Transc81_51_answ ,Transc81_52_answ ,Transc81_53_answ ,Transc81_54_answ ,Transc81_55_answ ,Transc81_56_answ ,Transc81_57_answ ,Transc81_58_answ ,Transc81_59_answ ,Transc81_60_answ ,Transc81_61_answ ,Transc81_62_answ ,Transc81_63_answ ,Transc81_64_answ ,Transc81_65_answ ,Transc81_66_answ ,Transc81_67_answ ,Transc81_68_answ ,Transc81_69_answ ,Transc81_70_answ ,Transc81_71_answ ,Transc81_72_answ ,Transc81_73_answ ,Transc81_74_answ ,Transc81_75_answ ,Transc81_76_answ ,Transc81_77_answ ,Transc81_78_answ ,Transc81_79_answ

,Transc81_80_answ ,Transc81_81_answ ,Sub_C_06_answ ,Mul_C_09_answ ,Mul_C_12_answ ,CB_street ,CB_street_score ,MAQ_GM_02 ,
Rey_rec1_7 ,Banuca8_CM_9_resp ,Banuca8_CM_10_resp ,Ideb ,Transc81_01 ,Transc81_02 ,Transc81_03 ,Transc81_04 ,Transc81_05 ,Transc81_06 ,Transc81_07 ,Transc81_08 ,Transc81_09 ,Transc81_10 ,Transc81_11 ,Transc81_12 ,Transc81_13 ,Transc81_14 ,Transc81_15 ,Transc81_16 ,Transc81_17 ,Transc81_18 ,Transc81_19 ,Transc81_20 ,Transc81_21 ,Transc81_22 ,Transc81_23 ,Transc81_24 ,Transc81_25 ,Transc81_26 ,Transc81_27 ,Transc81_28 ,Transc81_29 ,Transc81_30 ,Transc81_31 ,Transc81_32 ,Transc81_33 ,Transc81_34 ,Transc81_35 ,Transc81_36 ,Transc81_37 ,Transc81_38 ,Transc81_39 ,Transc81_40 ,Transc81_41 ,Transc81_42 ,Transc81_43 ,Transc81_44 ,Transc81_45 ,Transc81_46 ,Transc81_47 ,Transc81_48 ,Transc81_49 ,Transc81_50 ,Transc81_51 ,Transc81_52 ,Transc81_53 ,Transc81_54 ,Transc81_55 ,Transc81_56 ,Transc81_57 ,Transc81_58 ,Transc81_59 ,Transc81_60 ,Transc81_61 ,Transc81_62 ,Transc81_63 ,Transc81_64 ,Transc81_65 ,Transc81_66 ,Transc81_67 ,Transc81_68 ,Transc81_69 ,Transc81_70 ,Transc81_71 ,Transc81_72 ,Transc81_73 ,Transc81_74 ,Transc81_75 ,Transc81_76 ,Transc81_77 ,Transc81_78 ,Transc81_79 ,Transc81_80 ,Transc81_81 ,

3==>[72, 73, 847, 882, 1232, 1233, 1234, 1235, 1236, 1237, 1238, 1239, 1240, 1241, 1242, 1243, 1244, 1245, 1246, 1247, 1248, 1249, 1250, 1251, 1252, 1253, 1254, 1256, 1257, 1258, 1259, 1260, 1261, 1262, 1263, 1264, 1265, 1266, 1267, 1268, 1269, 1270, 1271, 1272, 1273, 1274, 1275, 1276, 1277, 1278, 1279, 1280, 1281, 1282, 1283, 1284, 1285, 1286, 1287, 1288, 1289, 1290, 1291, 1292, 1293, 1294, 1295, 1296, 1297, 1298, 1299, 1300, 1301, 1302, 1303, 1304, 1305, 1306, 1307, 1308, 1309, 1310, 1311, 1312, 1313, 1314, 1315, 1316, 1317, 1318, 1319, 1320, 1321, 1322, 1323, 1324, 1325, 1326, 1327, 1328, 1329, 1330, 1331, 1332, 1333, 1334, 1335, 1336, 1337, 1338, 1339, 1340, 1341, 1342, 1343, 1344, 1345, 1346, 1347, 1348, 1349, 1350, 1351]
Variable Names ==> CBCL_SomaticComplaints_SN ,CBCL_SomaticProblems_SN ,Banuca8_CM_3_resp ,Banuca9_RA_13_resp ,CBCL_1 ,CBCL_2 ,CBCL_3 ,CBCL_4 ,CBCL_5 ,CBCL_6 ,CBCL_7 ,CBCL_8 ,CBCL_9 ,CBCL_10 ,CBCL_11 ,CBCL_12 ,CBCL_13 ,CBCL_14 ,CBCL_15 ,CBCL_16 ,CBCL_17 ,CBCL_18 ,CBCL_19 ,CBCL_20 ,CBCL_21 ,CBCL_22 ,CBCL_23 ,CBCL_25 ,CBCL_26 ,CBCL_27 ,CBCL_28 ,CBCL_29 ,CBCL_30 ,CBCL_31 ,CBCL_32 ,CBCL_33 ,CBCL_34 ,CBCL_35 ,CBCL_36 ,CBCL_37 ,CBCL_38 ,CBCL_39 ,CBCL_40 ,CBCL_41 ,CBCL_42 ,CBCL_43 ,CBCL_44 ,CBCL_45 ,CBCL_46 ,CBCL_47 ,CBCL_48 ,CBCL_49 ,CBCL_50 ,CBCL_51 ,CBCL_52 ,CBCL_53 ,CBCL_54 ,CBCL_55 ,CBCL_56_a ,CBCL_56_b ,CBCL_56_c ,CBCL_56_d ,CBCL_56_e ,CBCL_56_f ,CBCL_56_g ,CBCL_56_h ,CBCL_57 ,CBCL_58 ,CBCL_59 ,CBCL_60 ,CBCL_61 ,CBCL_62 ,CBCL_63 ,CBCL_64 ,CBCL_65 ,CBCL_66 ,CBCL_67 ,CBCL_68 ,CBCL_69 ,CBCL_70 ,CBCL_71 ,CBCL_72 ,CBCL_73 ,CBCL_74 ,CBCL_75 ,CBCL_76 ,CBCL_77 ,CBCL_78 ,CBCL_79 ,CBCL_80 ,CBCL_81 ,CBCL_82 ,CBCL_83 ,CBCL_84

,CBCL_85 ,CBCL_86 ,CBCL_87 ,CBCL_88 ,CBCL_89 ,CBCL_90 ,CBCL_91 ,CBCL_92 ,CBCL_93 ,CBCL_94 ,CBCL_95 ,CBCL_96 ,CBCL_97 ,CBCL_98 ,CBCL_99 ,CBCL_100 ,CBCL_101 ,CBCL_102 ,CBCL_103 ,CBCL_104 ,CBCL_105 ,CBCL_106 ,CBCL_107 ,CBCL_108 ,CBCL_109 ,CBCL_110 ,CBCL_111 ,CBCL_112 ,CBCL_113 ,

24==>[81, 590, 591, 592, 593, 595, 596]
Variable Names ==> P_Digits_1digitcomparison ,Digits_arcsine_2 ,Digits_arcsine_3 ,Digits_arcsine_4 ,Digits_arcsine_6 ,Digits_arcsine_8 ,Digits_arcsine_9 ,

16==>[154, 307, 406, 485, 674, 675, 676, 737, 837, 839, 863, 871, 877, 878, 892, 893, 1255]
Variable Names ==> Transc81_05_answ ,Add_S_10_answ ,Mul_S_13_answ ,OV_CB_wm ,Orient_8 ,Orient_9 ,Orient_10 ,Rey_rec2_17 ,Banuca8_CM_3 ,Banuca8_CM_5 ,Banuca9_RA_9 ,Banuca9_RA_2_resp ,Banuca9_RA_8_resp ,Banuca9_RA_9_resp ,Fgnosias_RLH_escondido ,Fgnosias_RLH_dois_dedos ,CBCL_24 ,

8==>[235, 236, 240, 242, 243, 244, 245, 246, 247, 248, 249, 250, 251, 252, 253, 255, 257, 263, 264, 268, 270, 278, 299, 301, 302, 330, 356, 631]
Variable Names ==> NumRead_5 ,NumRead_6 ,NumRead_10 ,NumRead_12 ,NumRead_13 ,NumRead_14 ,NumRead_15 ,NumRead_16 ,NumRead_17 ,NumRead_18 ,NumRead_19 ,NumRead_20 ,NumRead_21 ,NumRead_22 ,NumRead_23 ,NumRead_25 ,NumRead_27 ,NumRead_R_5 ,NumRead_R_6 ,NumRead_R_10 ,NumRead_R_12 ,NumRead_R_21 ,Add_S_02_answ ,Add_S_04_answ ,Add_S_05_answ ,Add_C_06_answ ,Sub_S_05_answ ,TDE_Read_35 ,

4==>[254, 256, 258, 352, 448, 467, 530, 531, 532, 533, 535, 536, 539, 540, 541, 542, 544, 545, 546, 547, 548, 549, 550, 551, 552, 553, 554, 555, 556, 557, 560, 561, 562, 940, 1230]
Variable Names ==> NumRead_24 ,NumRead_26 ,NumRead_28 ,Sub_S_01_answ ,CB_car ,CB_car_score ,Pho_Elis_01 ,Pho_Elis_02 ,Pho_Elis_03 ,Pho_Elis_04 ,Pho_Elis_06 ,Pho_Elis_07 ,Pho_Elis_10 ,Pho_Elis_11 ,Pho_Elis_12 ,Pho_Elis_13 ,Pho_Elis_15 ,Pho_Elis_16 ,Pho_Elis_17 ,Pho_Elis_18 ,Pho_Elis_19 ,Pho_Elis_20 ,Pho_Elis_21 ,Pho_Elis_22 ,Pho_Elis_23 ,Pho_Elis_24 ,Pho_Elis_25 ,Pho_Elis_26 ,Pho_Elis_27 ,Pho_Elis_28 ,Five_Dig_Choos_E ,Five_Dig_Switch_E ,Pho_Elis_Percentage ,mult_comp_dp4 ,SNAP_25 ,

6==>[396, 414, 460, 479, 483, 489, 494, 500, 502, 543, 630, 632, 636, 640, 644, 649, 650, 651, 652, 654, 656, 658, 661, 662, 663, 664, 665, 774, 782, 852, 872, 974]
Variable Names ==> Mul_S_03_answ ,Mul_C_06_answ ,CB_Father_educ ,CB_housedl_score ,OV_CB_car ,OV_CB_iy ,OV_CB_car_score ,OV_CB_iy_score ,OV_Father_ed_level ,Pho_Elis_14 ,TDE_Read_34 ,TDE_Read_36 ,TDE_Read_40 ,TDE_Read_44 ,TDE_Read_48 ,TDE_Read_53 ,TDE_Read_54 ,TDE_Read_55 ,TDE_Read_56 ,TDE_Read_58 ,TDE_Read_60 ,TDE_Read_62 ,TDE_Read_65 ,TDE_Read_66 ,TDE_Read_67

,TDE_Read_68 ,TDE_Read_69 ,Banuca4_SS_8 ,Banuca4_SS_8_resp ,Banuca8_CM_8_resp ,Banuca9_RA_3_resp ,Consistencia_Lat_HYF ,

10==>[397, 1178, 1179, 1180, 1181, 1182, 1183, 1184, 1185, 1186, 1187, 1188, 1189, 1190, 1191, 1192, 1193, 1194, 1195, 1196, 1197, 1198, 1199, 1200, 1201, 1202, 1203, 1204, 1205]
Variable Names ==> Mul_S_04_answ ,Mul_S_01 ,Mul_S_02 ,Mul_S_03 ,Mul_S_04 ,Mul_S_05 ,Mul_S_06 ,Mul_S_07 ,Mul_S_08 ,Mul_S_09 ,Mul_S_10 ,Mul_S_11 ,Mul_S_12 ,Mul_S_13 ,Mul_S_14 ,Mul_S_15 ,Mul_C_01 ,Mul_C_02 ,Mul_C_03 ,Mul_C_04 ,Mul_C_05 ,Mul_C_06 ,Mul_C_07 ,Mul_C_08 ,Mul_C_09 ,Mul_C_10 ,Mul_C_11 ,Mul_C_12 ,Mul_C_13 ,

14==>[449, 468, 724, 725, 894, 896, 900, 903, 904, 905, 906, 907, 908, 910, 911, 912, 913, 914, 915, 916]
Variable Names ==> CB_computador ,CB_computer_score ,Rey_rec2_4 ,Rey_rec2_5 ,Num_Line_Paper_4 ,Num_Line_Paper_23 ,Num_Line_Paper_8 ,Num_Line_Paper_12 ,Num_Line_Paper_25 ,Num_Line_Paper_3 ,Num_Line_Paper_39 ,Num_Line_Paper_17 ,Num_Line_Paper_48 ,Num_Line_Paper_52 ,Num_Line_Paper_21 ,Num_Line_Paper_43 ,Num_Line_Paper_29 ,Num_Line_Paper_57 ,Num_Line_Paper_33 ,Num_Line_Paper_6 ,

22==>[968, 1056, 1521, 1522, 1523, 1524, 1525, 1526, 1527, 1528, 1529, 1530, 1531, 1533, 1534, 1535, 1536, 1537, 1538, 1539, 1540, 1541, 1543, 1544, 1546, 1547, 1548, 1549, 1550, 1551, 1552, 1553, 1554, 1555, 1556, 1557, 1558, 1559]
Variable Names ==> NM_Estereotipias ,hand_preferencia ,NM_Lat_H_1 ,NM_Lat_H_2 ,NM_Lat_H_3
,NM_Lat_H_result ,NM_Lat_Y_1 ,NM_Lat_Y_2 ,NM_Lat_Y_3 ,NM_Lat_Y_result ,NM_Lat_F_result ,NM_Moeda_D ,NM_Moeda_E ,NM_Pantonima2 ,NM_Pantonima3 ,NM_Pantonima4 ,NM_Pantonima5 ,NM_Pantonima6 ,SequenciaMotora ,InstrucesConflitantes ,GonoGo ,index_index ,Disdiadococinesia ,Oseretski ,Marcha ,NM_Tanden_frente ,NM_Tanden_tras ,NM_Romberg ,NM_Reacao_eq_frente ,NM_Reacao_eq_tras ,NM_Reacao_eq_lat ,NM_Corrida ,NM_Marcha_ponta_pe ,NM_Marcha_calcanhar,NM_Apoio_unipodal ,NM_Salto_palmas ,NM_Polichinelo ,NM_Coordenacao ,

23==>[978, 979, 980, 981, 982, 983, 984, 985, 986, 987, 988, 989, 990, 991, 992, 993, 994, 995, 996, 997, 998]
Variable Names ==> leitura_escrita2 ,matematica1 ,matematica2 ,Def_Intelec1 ,Def_Intelec2 ,externalizantes1 ,externalizantes2 ,internalizantes1 ,internalizantes2 ,autismo1 ,autismo2 ,TNVA1 ,TNVA2 ,Ansiedade1 ,Ansiedade2 ,DEL1 ,DEL2 ,TDAH1 ,TDAH2 ,Sindrome1 ,Psiquiatrico1 ,

12==>[1000, 1485, 1486, 1487, 1488, 1489, 1490, 1491, 1492, 1493, 1494, 1495,

1496, 1497, 1498, 1499, 1500, 1501, 1502, 1503, 1504, 1505, 1506, 1507, 1508, 1509, 1510, 1511, 1512, 1513, 1514, 1515, 1516, 1517, 1518, 1519, 1520]
Variable Names ==> wisc_reduzido_final ,Raven_A_1 ,Raven_A_2 ,Raven_A_3 ,Raven_A_4 ,Raven_A_5 ,Raven_A_6 ,Raven_A_7 ,Raven_A_8 ,Raven_A_9 ,Raven_A_10 ,Raven_A_11 ,Raven_A_12 ,Raven_AB_1 ,Raven_AB_2 ,Raven_AB_3 ,Raven_AB_4 ,Raven_AB_5 ,Raven_AB_6 ,Raven_AB_7 ,Raven_AB_8 ,Raven_AB_9 ,Raven_AB_10 ,Raven_AB_11 ,
Raven_AB_12 ,Raven_B_1 ,Raven_B_2 ,Raven_B_3 ,Raven_B_4 ,Raven_B_5 ,Raven_B_6 ,Raven_B_7 ,Raven_B_8 ,Raven_B_9 ,Raven_B_10 ,Raven_B_11 ,Raven_B_12 ,

18==>[1057, 1058, 1059, 1060, 1061, 1062, 1063, 1064, 1065, 1066, 1067, 1068, 1069, 1070, 1071, 1072, 1073, 1074, 1075, 1076, 1077, 1078, 1079, 1080, 1081, 1082, 1083, 1084, 1085, 1086, 1087, 1088, 1089, 1090, 1091, 1092, 1093, 1094, 1095, 1096]
Variable Names ==> Transc_1 ,Transc_2 ,Transc_3 ,Transc_4 ,Transc_5 ,Transc_6 ,Transc_7 ,Transc_8 ,Transc_9 ,Transc_10 ,Transc_11 ,Transc_12 ,Transc_13 ,Transc_14 ,Transc_15 ,Transc_16 ,Transc_17 ,Transc_18 ,Transc_19 ,Transc_20 ,Transc_21 ,Transc_22 ,Transc_23 ,Transc_24 ,Transc_25 ,Transc_26 ,Transc_27 ,Transc_28 ,Transc_29 ,Transc_30 ,Transc_31 ,Transc_32 ,Transc_33 ,Transc_34 ,Transc_35 ,Transc_36 ,Transc_37 ,Transc_38 ,Transc_39 ,Transc_40 ,

11==>[1352, 1353, 1354, 1355, 1356, 1357, 1358, 1359, 1360, 1361, 1362, 1363, 1364, 1365, 1366, 1367, 1368, 1369, 1370, 1371, 1372, 1373, 1374, 1375, 1376, 1377, 1378, 1379, 1380, 1381, 1382, 1383, 1384, 1385, 1386, 1387, 1388, 1389, 1390, 1391, 1392, 1393, 1394, 1395, 1396, 1397, 1398, 1399, 1400, 1401, 1402, 1403, 1404, 1405, 1406, 1407, 1408, 1409, 1410, 1411, 1412, 1413, 1414, 1415, 1416, 1417, 1418, 1419, 1420, 1421, 1422, 1423, 1424]
Variable Names ==> TDE_Spell_name ,TDE_Spell_1 ,TDE_Spell_2 ,TDE_Spell_3 ,TDE_Spell_4 ,TDE_Spell_5 ,TDE_Spell_6 ,TDE_Spell_7 ,TDE_Spell_8 ,TDE_Spell_9 ,TDE_Spell_10 ,TDE_Spell_11 ,TDE_Spell_12 ,TDE_Spell_13 ,TDE_Spell_14 ,TDE_Spell_15 ,TDE_Spell_16 ,TDE_Spell_17 ,TDE_Spell_18 ,TDE_Spell_19 ,TDE_Spell_20 ,TDE_Spell_21 ,TDE_Spell_22 ,TDE_Spell_23 ,TDE_Spell_24 ,TDE_Spell_25 ,TDE_Spell_26 ,TDE_Spell_27 ,TDE_Spell_28 ,TDE_Spell_29 ,TDE_Spell_30 ,TDE_Spell_31 ,TDE_Spell_32 ,TDE_Spell_33 ,TDE_Spell_34 ,TDE_Arit_oral_1 ,TDE_Arit_oral_2 ,TDE_Arit_oral_3 ,TDE_Arit_1 ,TDE_Arit_2 ,TDE_Arit_3 ,TDE_Arit_4 ,TDE_Arit_5 ,TDE_Arit_6 ,TDE_Arit_7 ,TDE_Arit_8 ,TDE_Arit_9 ,TDE_Arit_10 ,TDE_Arit_11 ,TDE_Arit_12 ,TDE_Arit_13 ,TDE_Arit_14 ,TDE_Arit_15 ,TDE_Arit_16 ,TDE_Arit_17 ,TDE_Arit_18 ,TDE_Arit_19 ,TDE_Arit_20 ,TDE_Arit_21 ,TDE_Arit_22 ,TDE_Arit_23 ,TDE_Arit_24 ,TDE_Arit_25 ,TDE_Arit_26 ,TDE_Arit_27 ,TDE_Arit_28 ,TDE_Arit_29 ,TDE_Arit_30 ,TDE_Arit_31 ,TDE_Arit_32 ,TDE_Arit_33 ,TDE_Arit_34 ,TDE_Arit_35

G.2 Dataset 149

Leader variables (501) 0==>Age_months

3==>RavenNovo_junto_Adulto

5==>ParaCOM_QI

6==>Vocab_PP_revisado

7==>Cubos_PP_revisado

10==>OP

11==>IMO_RD

12==>VP

16==>Digitos_Pond

20==>Compl_fig_Pond

21==>Arranj_fig_Pond

22==>Armar_obj_Pond

27==>Racioc_Palavras_Pond

30==>Cancel_Pond

31==>Nine_RH_mean

35==>Nine_Relative_handedness

36==>fracao_w

37==>Fluenc_Arit_CalcFeitos

38==>Fluenc_Arit_CalcPulados

39==>Fluenc_Arit_Tempo

40==>Fluenc_Arit_Erros

44==>Nscreener_Nsimb_Made

46==>Reading_Fluency_Time

47==>Reading_Fluency_LP

49==>Five_Dig_Read_RT

51==>Five_Dig_Choos_RT

56==>Multidigits_T_Adicao

57==>Multidigits_T_Sub

59==>Warring_multiplicacao

62==>Leit_Pseudo_40

63==>Repet_Pseudo_15

64==>Supressao_Fon_30

65==>Repet_Pseudo_40

66==>RAN_1

67==>RAN_2

68==>RAN_3

70==>RAN_1_erros

71==>RAN_2_erros
72==>RAN_3_erros
73==>RAN_4_erros
74==>CBCL_SomaticComplaints_SN
76==>Add_S_Time
77==>Add_C_Time
78==>Sub_S_Time
79==>Sub_C_Time
82==>P_Dots_ref32
83==>P_Digits_1digitcomparison
84==>SNAP_Mean_ADHD_inattention
87==>SNAP_Mean_ODD
89==>Verbal_Fluency_An_Errors
90==>Five_Points_orig
91==>Five_Points_repet
93==>RAVLT_LA_1
100==>RAVLT_LA_7
101==>RAVLT_Reconhec
106==>SRT_mean
112==>Transc_R_1
115==>Transc_R_4
117==>Transc_R_6
120==>Transc_R_9
125==>Transc_R_14
129==>Transc_R_18
152==>Transc81_01_answ
153==>Transc81_02_answ
154==>Transc81_03_answ
155==>Transc81_04_answ
156==>Transc81_05_answ
160==>Transc81_09_answ
169==>Transc81_18_answ
170==>Transc81_19_answ
171==>Transc81_20_answ
179==>Transc81_28_answ
233==>NumRead_1
234==>NumRead_2
235==>NumRead_3
236==>NumRead_4

237==>NumRead_5
239==>NumRead_7
241==>NumRead_9
245==>NumRead_13
248==>NumRead_16
249==>NumRead_17
252==>NumRead_20
261==>NumRead_R_1
262==>NumRead_R_2
263==>NumRead_R_3
264==>NumRead_R_4
269==>NumRead_R_9
272==>NumRead_R_12
275==>NumRead_R_15
276==>NumRead_R_17
277==>NumRead_R_18
278==>NumRead_R_19
279==>NumRead_R_20
280==>NumRead_R_21
283==>NumRead_R_24
286==>NumRead_R_27
287==>NumRead_R_28
288==>Add_S_01
289==>Add_S_02
290==>Add_S_03
295==>Add_S_08
300==>Add_S_01_answ
301==>Add_S_02_answ
303==>Add_S_04_answ
309==>Add_S_10_answ
311==>Add_S_12_answ
312==>Add_C_01
314==>Add_C_03
315==>Add_C_04
316==>Add_C_05
318==>Add_C_07
320==>Add_C_09
323==>Add_C_12
329==>Add_C_03_answ

332==>Add_C_06_answ
334==>Add_C_08_answ
342==>Sub_S_01
343==>Sub_S_02
346==>Sub_S_05
349==>Sub_S_08
350==>Sub_S_09
355==>Sub_S_02_answ
356==>Sub_S_03_answ
358==>Sub_S_05_answ
360==>Sub_S_07_answ
366==>Sub_C_01
376==>Sub_C_11
381==>Sub_C_01_answ
382==>Sub_C_02_answ
392==>Sub_C_12_answ
397==>Mul_S_02_answ
398==>Mul_S_03_answ
400==>Mul_S_05_answ
401==>Mul_S_06_answ
411==>Mul_C_01_answ
412==>Mul_C_02_answ
413==>Mul_C_03_answ
415==>Mul_C_05_answ
419==>Mul_C_09_answ
421==>Mul_C_11_answ
424==>Prob_01
425==>Prob_02
426==>Prob_03
428==>Prob_05
430==>Prob_07
431==>Prob_08
432==>Prob_09
433==>Prob_10
435==>Prob_12
437==>Prob_R_2
439==>Prob_R_4
445==>Prob_R_10
448==>CB_bath

449==>CB_maid

450==>CB_car

451==>CB_computador

452==>CB_dw

453==>CB_fridge

454==>CB_freezer

455==>CB_wm

457==>CB_mcw

458==>CB_moto

459==>CB_drm

462==>CB_Father_educ

464==>CB_People_House

465==>CB_People_bedroom

466==>CB_income

482==>OV_CB_tv

483==>OV_CB_radio

484==>OV_CB_bath

485==>OV_CB_car

486==>OV_CB_hm

487==>OV_CB_wm

488==>OV_CB_dvd

489==>OV_CB_ref

490==>OV_CB_freezer

491==>OV_CB_iy

492==>OV_CB_np

498==>OV_CB_wm_score

500==>OV_CB_ref_score

505==>MAQ_GM_01

506==>MAQ_GM_02

508==>MAQ_GM_04

509==>MAQ_EC_01

510==>MAQ_EC_02

511==>MAQ_EC_03

516==>MAQ_DC_04

517==>MAQ_WC_01

519==>MAQ_WC_03

521==>MAQ_MC_01

523==>MAQ_MC_03

525==>MAQ_HW_01

526==>MAQ_HW_02

527==>MAQ_HW_03

528==>MAQ_HW_04

529==>LPI_Reg_Porcentagem

532==>Pho_Elis_01

533==>Pho_Elis_02

534==>Pho_Elis_03

535==>Pho_Elis_04

537==>Pho_Elis_06

539==>Pho_Elis_08

540==>Pho_Elis_09

541==>Pho_Elis_10

542==>Pho_Elis_11

545==>Pho_Elis_14

546==>Pho_Elis_15

549==>Pho_Elis_18

550==>Pho_Elis_19

558==>Pho_Elis_27

560==>Five_Dig_Read_E

561==>Five_Dig_Count_E

562==>Five_Dig_Choos_E

565==>Rey_copy_1

566==>Rey_copy_2

569==>Rey_copy_5

570==>Rey_copy_6

571==>Rey_copy_7

572==>Rey_copy_8

573==>Rey_copy_9

575==>Rey_copy_11

578==>Rey_copy_14

581==>Rey_copy_17

582==>Rey_copy_18

583==>Est_median_1

584==>Est_median_2

593==>Est_median_56

599==>Est_RT_mean_5

607==>Digits_error_1

608==>Digits_error_2

609==>Digits_error_3

610==>Digits_error_4

611==>Digits_error_6

612==>Digits_error_7

613==>Digits_error_8

614==>Digits_error_9

615==>Digits_arcsine_1

620==>Digits_arcsine_7

623==>TDE_Read_1

624==>TDE_Read_2

625==>TDE_Read_3

627==>TDE_Read_5

628==>TDE_Read_6

629==>TDE_Read_7

630==>TDE_Read_8

633==>TDE_Read_11

634==>TDE_Read_12

637==>TDE_Read_15

642==>TDE_Read_20

646==>TDE_Read_24

651==>TDE_Read_29

656==>TDE_Read_34

658==>TDE_Read_36

675==>TDE_Read_53

676==>TDE_Read_54

684==>TDE_Read_62

687==>TDE_Read_65

693==>Orient_1

696==>Orient_4

697==>Orient_5

698==>Orient_6

699==>Orient_7

702==>Orient_10

705==>Fgnosia_RH_1

706==>Fgnosia_RH_2

707==>Fgnosia_RH_3

708==>Fgnosia_RH_4

709==>Fgnosia_RH_5

710==>Fgnosia_RH_6

712==>Fgnosia_RH_8

713==>Fgnosia_RH_9
715==>Fgnosia_RH_11
716==>Fgnosia_RH_12
717==>Fgnosia_LH_1
718==>Fgnosia_LH_2
719==>Fgnosia_LH_3
720==>Fgnosia_LH_4
721==>Fgnosia_LH_5
722==>Fgnosia_LH_6
723==>Fgnosia_LH_7
725==>Fgnosia_LH_9
727==>Fgnosia_LH_11
729==>Rey_rec1_1
731==>Rey_rec1_3
734==>Rey_rec1_6
736==>Rey_rec1_8
737==>Rey_rec1_9
738==>Rey_rec1_10
739==>Rey_rec1_11
743==>Rey_rec1_15
744==>Rey_rec1_16
747==>Rey_rec2_1
750==>Rey_rec2_4
752==>Rey_rec2_6
754==>Rey_rec2_8
755==>Rey_rec2_9
756==>Rey_rec2_10
757==>Rey_rec2_11
760==>Rey_rec2_14
763==>Rey_rec2_17
765==>Banuca1_CP_1
766==>Banuca1_CP_2
767==>Banuca1_CP_3
768==>Banuca1_CP_4
769==>Banuca1_CP_5
770==>Banuca1_CP_6
771==>Banuca2_AS_1
772==>Banuca2_AS_2
774==>Banuca2_AS_4

775==>Banuca2_AS_5

778==>Banuca2_AS_8

779==>Banuca2_AS_1_resp

780==>Banuca2_AS_2_resp

781==>Banuca2_AS_3_resp

782==>Banuca2_AS_4_resp

787==>Banuca3_C_1

793==>Banuca4_SS_1

794==>Banuca4_SS_2

795==>Banuca4_SS_3

796==>Banuca4_SS_4

801==>Banuca4_SS_1_resp

802==>Banuca4_SS_2_resp

803==>Banuca4_SS_3_resp

809==>Banuca5_LN_1

810==>Banuca5_LN_2

811==>Banuca5_LN_3

812==>Banuca5_LN_4

813==>Banuca5_LN_5

815==>Banuca5_LN_7

816==>Banuca5_LN_8

817==>Banuca5_LN_1_resp

818==>Banuca5_LN_2_resp

819==>Banuca5_LN_3_resp

820==>Banuca5_LN_4_resp

821==>Banuca5_LN_5_resp

824==>Banuca5_LN_8_resp

825==>Banuca6_CN_1

827==>Banuca6_CN_3

828==>Banuca6_CN_4

830==>Banuca6_CN_6

835==>Banuca6_CN_1_resp

836==>Banuca6_CN_2_resp

837==>Banuca6_CN_3_resp

840==>Banuca6_CN_6_resp

845==>Banuca7_RN_1

846==>Banuca7_RN_2

847==>Banuca7_RN_3

848==>Banuca7_RN_4

849==>Banuca7_RN_5
853==>Banuca7_RN_1_resp
854==>Banuca7_RN_2_resp
855==>Banuca7_RN_3_resp
856==>Banuca7_RN_4_resp
857==>Banuca7_RN_5_resp
864==>Banuca8_CM_4
867==>Banuca8_CM_7
870==>Banuca8_CM_10
877==>Banuca8_CM_7_resp
878==>Banuca8_CM_8_resp
881==>Banuca9_RA_1
887==>Banuca9_RA_7
888==>Banuca9_RA_8
896==>Banuca9_RA_1_resp
902==>Banuca9_RA_7_resp
904==>Banuca9_RA_9_resp
917==>Fgnosias_RLH_visivel
918==>Fgnosias_RLH_escondido
920==>Num_Line_Paper_4
921==>Num_Line_Paper_79
922==>Num_Line_Paper_23
923==>Num_Line_Paper_84
924==>Num_Line_Paper_61
936==>Num_Line_Paper_52
943==>Num_Line_Paper_72
946==>Span_PP_1
947==>Span_PP_2
948==>Span_PP_3
949==>Span_PP_4
950==>Span_PP_5
951==>Span_PP_6
955==>mult_comp_med2
960==>mult_comp_med7
982==>FT_D_1
989==>NM_Fgnosia_RH_2
991==>NM_Fgnosia_LH_1
992==>NM_Fgnosia_LH_2
999==>Consistencia_Lat_H

1001==>SES_juntado
1003==>Sex
1004==>School_type
1005==>wisc_reduzido_final
1006==>preferencia_manual
1013==>Corsi_F_4_1
1017==>Corsi_F_6_1
1019==>Corsi_F_7_1
1023==>Corsi_B_2_1
1029==>Corsi_B_5_1
1031==>Corsi_B_6_1
1033==>Corsi_B_7_1
1043==>Dspan_F_4_1
1047==>Dspan_F_6_1
1051==>Dspan_F_8_1
1057==>Dspan_B_3_1
1061==>Dspan_B_5_1
1063==>Dspan_B_6_1
1187==>Mul_S_01
1193==>Mul_S_07
1204==>Mul_C_03
1208==>Mul_C_07
1215==>SNAP_1
1216==>SNAP_2
1217==>SNAP_3
1218==>SNAP_4
1219==>SNAP_5
1220==>SNAP_6
1221==>SNAP_7
1222==>SNAP_8
1223==>SNAP_9
1224==>SNAP_10
1225==>SNAP_11
1226==>SNAP_12
1227==>SNAP_13
1228==>SNAP_14
1229==>SNAP_15
1230==>SNAP_16
1231==>SNAP_17

1232==>SNAP_18

1233==>SNAP_19

1234==>SNAP_20

1235==>SNAP_21

1236==>SNAP_22

1237==>SNAP_23

1238==>SNAP_24

1239==>SNAP_25

1240==>SNAP_26

1241==>CBCL_1

1242==>CBCL_2

1243==>CBCL_3

1244==>CBCL_4

1245==>CBCL_5

1247==>CBCL_7

1249==>CBCL_9

1250==>CBCL_10

1251==>CBCL_11

1253==>CBCL_13

1254==>CBCL_14

1257==>CBCL_17

1258==>CBCL_18

1259==>CBCL_19

1260==>CBCL_20

1262==>CBCL_22

1265==>CBCL_25

1271==>CBCL_31

1274==>CBCL_34

1276==>CBCL_36

1277==>CBCL_37

1284==>CBCL_44

1287==>CBCL_47

1289==>CBCL_49

1293==>CBCL_53

1305==>CBCL_58

1310==>CBCL_63

1316==>CBCL_69

1318==>CBCL_71

1323==>CBCL_76

1337==>CBCL_90

1349==>CBCL_102

1361==>TDE_Spell_name

1362==>TDE_Spell_1

1367==>TDE_Spell_6

1368==>TDE_Spell_7

1369==>TDE_Spell_8

1370==>TDE_Spell_9

1373==>TDE_Spell_12

1374==>TDE_Spell_13

1380==>TDE_Spell_19

1382==>TDE_Spell_21

1389==>TDE_Spell_28

1396==>TDE_Arit_oral_1

1398==>TDE_Arit_oral_3

1400==>TDE_Arit_2

1401==>TDE_Arit_3

1403==>TDE_Arit_5

1405==>TDE_Arit_7

1407==>TDE_Arit_9

1412==>TDE_Arit_14

1413==>TDE_Arit_15

1416==>TDE_Arit_18

1418==>TDE_Arit_20

1422==>TDE_Arit_24

1426==>TDE_Arit_28

1494==>Raven_A_1

1530==>NM_Lat_H_1

1541==>NM_Pantonima1

1547==>SequenciaMotora

1551==>Oponencia

1553==>Oseretski

1554==>Impersistencia_motora

1556==>NM_Tanden_frente

1562==>NM_Corrida

List of cluster variables

192==>[0, 1, 2]

Variable Names ==> Age_months ,Age_years ,Grade ,

409==>[3, 4]
Variable Names ==> RavenNovo_junto_Adulto ,Inteligencia_FINAL_juntos ,

271==>[5]
Variable Names ==> ParaCOM_QI ,

408==>[6, 8, 9, 13, 15, 17, 18, 19]
Variable Names ==> Vocab_PP_revisado ,QI_T ,CV ,QI_V ,Semel_PP_Triagem ,Semelh_Pond ,Inform_Pond ,Compreen_Pon ,

412==>[7]
Variable Names ==> Cubos_PP_revisado ,

411==>[10, 14, 23]
Variable Names ==> OP ,QI_E ,Racioc_Matric_Pon ,

436==>[11, 25, 26]
Variable Names ==> IMO_RD ,Arit_Pond ,Seq_N_Let_Pon ,

414==>[12, 28, 29]
Variable Names ==> VP ,Codigos_Pond ,Proc_Simb_Pond ,

441==>[16]
Variable Names ==> Digitos_Pond ,

413==>[20]
Variable Names ==> Compl_fig_Pond ,

208==>[21, 162, 163, 164, 165, 166, 167, 168]
Variable Names ==> Arranj_fig_Pond ,Transc81_11_answ ,Transc81_12_answ ,Transc81_13_answ ,Transc81_14_answ ,Transc81_15_answ ,Transc81_16_answ ,Transc81_17_answ ,

410==>[22, 24]
Variable Names ==> Armar_obj_Pond ,Conc_Fig_Pond ,

440==>[27, 748]
Variable Names ==> Racioc_Palavras_Pond ,Rey_rec2_2 ,

148==>[30, 55, 88, 773, 823, 829, 832, 841, 879, 882, 884, 899, 903, 952, 962, 973, 974, 975, 976, 977, 978, 979, 980]
Variable Names ==> Cancel_Pond ,Numb_Read_81 ,Verbal_Fluency_An_Corrects ,Banuca2_AS_3
,Banuca5_LN_7_resp ,Banuca6_CN_5 ,Banuca6_CN_8 ,Banuca6_CN_7_resp ,Banuca8_CM_9_resp ,Banuca9_RA_2 ,Banuca9_RA_4 ,Banuca9_RA_4_resp ,Banuca9_RA_8_resp ,Span_PP_7 ,mult_comp_med9 ,mult_comp_acc2 ,mult_comp_acc3 ,mult_comp_acc4 ,mult_comp_acc5 ,mult_comp_acc6 ,mult_comp_acc7 ,mult_comp_acc8 ,mult_comp_acc9 ,

157==>[31, 32, 33, 34]
Variable Names ==> Nine_RH_mean ,Nine_DH_mean ,Nine_LH_mean ,Nine_NDH_mean ,

428==>[35]
Variable Names ==> Nine_Relative_handedness ,

204==>[36, 826, 1434, 1435, 1436, 1437, 1438, 1439, 1440, 1441, 1442, 1443, 1444, 1445, 1446, 1447, 1448, 1449, 1450, 1451, 1452, 1453, 1454, 1455, 1456, 1457, 1458, 1459, 1460, 1461, 1462, 1463, 1464, 1465, 1466, 1467, 1468, 1469, 1470, 1471, 1472, 1473, 1474, 1475, 1476, 1477, 1478, 1479, 1480, 1481, 1482, 1483, 1484, 1485, 1486, 1487, 1488, 1489, 1490, 1491, 1492, 1493]
Variable Names ==> fracao_w ,Banuca6_CN_2 ,LPI_Reg_01 ,LPI_Reg_02 ,LPI_Reg_03 ,LPI_Reg_04 ,LPI_Reg_05 ,LPI_Reg_06 ,LPI_Reg_07 ,LPI_Reg_08 ,LPI_Reg_09 ,LPI_Reg_10 ,LPI_Reg_11 ,LPI_Reg_12 ,LPI_Reg_13 ,LPI_Reg_14 ,LPI_Reg_15 ,LPI_Reg_16 ,LPI_Reg_17 ,LPI_Reg_18 ,LPI_Reg_19 ,LPI_Reg_20 ,LPI_Irreg_01 ,LPI_Irreg_02 ,LPI_Irreg_03 ,LPI_Irreg_04 ,LPI_Irreg_05 ,LPI_Irreg_06 ,LPI_Irreg_07 ,LPI_Irreg_08 ,LPI_Irreg_09 ,LPI_Irreg_10 ,LPI_Irreg_11 ,LPI_Irreg_12 ,LPI_Irreg_13 ,LPI_Irreg_14 ,LPI_Irreg_15 ,LPI_Irreg_16 ,LPI_Irreg_17 ,LPI_Irreg_18 ,LPI_Irreg_19 ,LPI_Irreg_20 ,LPI_Pseud_01 ,LPI_Pseud_02 ,LPI_Pseud_03 ,LPI_Pseud_04 ,LPI_Pseud_05 ,LPI_Pseud_06 ,LPI_Pseud_07 ,LPI_Pseud_08 ,LPI_Pseud_09 ,LPI_Pseud_10 ,LPI_Pseud_11 ,LPI_Pseud_12 ,LPI_Pseud_13 ,LPI_Pseud_14 ,LPI_Pseud_15 ,LPI_Pseud_16 ,LPI_Pseud_17 ,LPI_Pseud_18 ,LPI_Pseud_19 ,LPI_Pseud_20 ,

149==>[37, 41, 42, 43, 58, 102, 104, 105, 338, 339, 340, 341, 372, 387, 388, 389, 391, 393, 394, 395, 407, 409, 410, 891, 893, 894, 906, 908, 909, 911, 912, 913, 914, 915, 916, 953]
Variable Names ==> Fluenc_Arit_CalcFeitos ,Fluenc_Arit_Corretas ,Nscreener_Simb_Made ,Nscreener_Simb_TC ,Multidigits_T_Mult ,Stroop_Vic_Color ,Stroop_Vic_Incongr ,Stroop_Vic_Interf ,Add_C_12_answ ,Add_C_13_answ ,Add_C_14_answ ,Add_C_15_answ ,Sub_C_07 ,Sub_C_07_answ ,Sub_C_08_answ ,Sub_C_09_answ ,Sub_C_11_answ ,Sub_C_13_answ ,Sub_C_14_answ ,Sub_C_15_answ ,Mul_S_12_answ ,Mul_S_14_answ ,Mul_S_15_answ ,Banuca9_RA_11 ,Banuca9_RA_13 ,Banuca9_RA_14 ,Banuca9_RA_11_resp ,Banuca9_RA_13_resp ,Banuca9_RA_14_resp ,Fgnosia_RH_visivel ,Fgnosia_RH_escondido ,Fgnosia_RH_dois_dedos ,Fgnosia_LH_visivel ,Fgnosia_LH_escondido ,Fgnosia_LH_dois_dedos ,Span_PP_8 ,

52==>[38, 416]
Variable Names ==> Fluenc_Arit_CalcPulados ,Mul_C_06_answ ,

283==>[39, 740]
Variable Names ==> Fluenc_Arit_Tempo ,Rey_rec1_12 ,

11==>[40, 631, 639, 674]
Variable Names ==> Fluenc_Arit_Erros ,TDE_Read_9 ,TDE_Read_17 ,TDE_Read_52
,

33==>[44, 45, 48, 396, 831]
Variable Names ==> Nscreener_Nsimb_Made ,
Nscreener_Nsimb_TC ,Reading_Fluency_Errors ,
Mul_S_01_answ ,Banuca6_CN_7 ,

267==>[46]
Variable Names ==> Reading_Fluency_Time ,

146==>[47, 800, 875, 883, 956, 957, 958, 959, 964, 965, 967, 968, 971]
Variable Names ==> Reading_Fluency_LP ,Banuca4_SS_8 ,Banuca8_CM_5_resp
,Banuca9_RA_3 ,mult_comp_med3 ,mult_comp_med4 ,mult_comp_med5 ,mult_comp_med6
,mult_comp_dp2 ,mult_comp_dp3 ,mult_comp_dp5 ,mult_comp_dp6 ,mult_comp_dp9
,

189==>[49, 50]
Variable Names ==> Five_Dig_Read_RT ,Five_Dig_Cout_RT ,

188==>[51, 52, 53, 54]
Variable Names ==> Five_Dig_Choos_RT ,Five_Dig_Switch_RT ,
Five_Dig_Inhibit_RT ,Five_Dig_Flexib_RT ,

426==>[56]
Variable Names ==> Multidigits_T_Adicao ,

140==>[57, 814, 822, 834, 844, 861, 871, 885, 900]
Variable Names ==> Multidigits_T_Sub ,Banuca5_LN_6 ,Banuca5_LN_6_resp ,Banuca6_CN_10
,Banuca6_CN_10_resp ,Banuca8_CM_1 ,Banuca8_CM_1_resp ,
Banuca9_RA_5 ,Banuca9_RA_5_resp ,

147==>[59, 60, 61, 92, 103, 111, 694, 695, 703, 704, 944]
Variable Names ==> Warring_multiplicacao ,Warring_operacoes ,Warring_cotidiano ,
Five_Points_erros ,Stroop_Vic_ColorW ,
Verbal_Fluency_An_Repetition ,Orient_2 ,Orient_3 ,
Orient_11 ,Orient_12 ,Num_Line_Paper_Ajust_Linear ,

152==>[62, 375, 786, 862, 863, 872, 897, 910]
Variable Names ==> Leit_Pseudo_40 ,Sub_C_10 ,Banuca2_AS_8_resp ,Banuca8_CM_2
,Banuca8_CM_3 ,Banuca8_CM_2_resp ,Banuca9_RA_2_resp ,Banuca9_RA_15_resp
,

404==>[63]
Variable Names ==> Repet_Pseudo_15 ,

405==>[64]
Variable Names ==> Supressao_Fon_30 ,

144==>[65, 753, 761, 954, 963, 972]
Variable Names ==> Repet_Pseudo_40 ,Rey_rec2_7 ,Rey_rec2_15 ,mult_comp_med1 ,mult_comp_dp1 ,mult_comp_acc1 ,

54==>[66, 110, 333, 385]
Variable Names ==> RAN_1 ,wrsquared ,Add_C_07_answ ,Sub_C_05_answ ,

228==>[67, 69]
Variable Names ==> RAN_2 ,RAN_4 ,

215==>[68, 386, 994]
Variable Names ==> RAN_3 ,Sub_C_06_answ ,NM_Estereotipias ,

184==>[70, 399]
Variable Names ==> RAN_1_erros ,Mul_S_04_answ ,

406==>[71]
Variable Names ==> RAN_2_erros ,

407==>[72]
Variable Names ==> RAN_3_erros ,

389==>[73]
Variable Names ==> RAN_4_erros ,

237==>[74, 75, 1291, 1296, 1297, 1298, 1299, 1300, 1301, 1302]
Variable Names ==> CBCL_SomaticComplaints_SN ,CBCL_SomaticProblems_SN ,CBCL_51 ,CBCL_56_a ,CBCL_56_b ,CBCL_56_c ,CBCL_56_d ,CBCL_56_e ,CBCL_56_f ,CBCL_56_g ,

193==>[76]
Variable Names ==> Add_S_Time ,

444==>[77]
Variable Names ==> Add_C_Time ,

88==>[78, 80]
Variable Names ==> Sub_S_Time ,Mul_S_Time ,

89==>[79, 81]
Variable Names ==> Sub_C_Time ,Mul_C_Time ,

76==>[82, 507, 513, 514, 515]
Variable Names ==> P_Dots_ref32 ,MAQ_GM_03 ,MAQ_DC_01 ,MAQ_DC_02 , MAQ_DC_03 ,

445==>[83, 616, 617, 618, 619, 621, 622]
Variable Names ==> P_Digits_1digitcomparison ,Digits_arcsine_2 ,Digits_arcsine_3 ,Digits_arcsine_4 ,Digits_arcsine_6 ,Digits_arcsine_8 ,Digits_arcsine_9 ,

456==>[84, 85, 86]
Variable Names ==> SNAP_Mean_ADHD_inattention , SNAP_Mean_ADHD_hyperactivity ,SNAP_Mean_ADHD_combined ,

457==>[87]
Variable Names ==> SNAP_Mean_ODD ,

275==>[89, 124, 127, 128]
Variable Names ==> Verbal_Fluency_An_Errors ,Transc_R_13 ,Transc_R_16 ,Transc_R_17 ,

205==>[90, 161, 1106, 1107, 1108, 1109, 1110, 1111, 1112, 1113, 1114, 1115, 1116, 1117, 1118, 1119, 1120, 1121, 1122, 1123, 1124, 1125, 1126, 1127, 1128, 1129, 1130, 1131, 1132, 1133, 1134, 1135, 1136, 1137, 1138, 1139, 1140, 1141, 1142, 1143, 1144, 1145, 1146, 1147, 1148, 1149, 1150, 1151, 1152, 1153, 1154, 1155, 1156, 1157, 1158, 1159, 1160, 1161, 1162, 1163, 1164, 1165, 1166, 1167, 1168, 1169, 1170, 1171, 1172, 1173, 1174, 1175, 1176, 1177, 1178, 1179, 1180, 1181, 1182, 1183, 1184, 1185, 1186]
Variable Names ==> Five_Points_orig ,Transc81_10_answ ,Transc81_01 ,Transc81_02 ,Transc81_03 ,Transc81_04 ,Transc81_05 ,Transc81_06 ,Transc81_07 ,Transc81_08 ,Transc81_09 ,Transc81_10 ,Transc81_11 ,Transc81_12 ,Transc81_13 ,Transc81_14 ,Transc81_15 ,Transc81_16 ,Transc81_17 ,Transc81_18 ,Transc81_19 ,Transc81_20 ,Transc81_21 ,Transc81_22 ,Transc81_23 ,Transc81_24 ,Transc81_25 ,Transc81_26 ,Transc81_27 ,Transc81_28 ,Transc81_29 ,Transc81_30 ,Transc81_31 ,Transc81_32 ,Transc81_33 ,Transc81_34 ,Transc81_35 ,Transc81_36 ,Transc81_37 ,Transc81_38 ,Transc81_39 ,Transc81_40 ,Transc81_41 ,Transc81_42 ,Transc81_43 ,Transc81_44 ,Transc81_45 ,Transc81_46 ,Transc81_47 ,Transc81_48 ,Transc81_49 ,Transc81_50 ,Transc81_51 ,Transc81_52 ,Transc81_53 ,Transc81_54 ,Transc81_55 ,Transc81_56 ,Transc81_57 ,Transc81_58 ,Transc81_59 ,Transc81_60 ,Transc81_61 ,Transc81_62 ,Transc81_63 ,Transc81_64 ,Transc81_65 ,Transc81_66 ,Transc81_67 ,Transc81_68 ,Transc81_69 ,Transc81_70 ,Transc81_71 ,Transc81_72 ,Transc81_73 ,Transc81_74 ,Transc81_75 ,Transc81_76 ,Transc81_77 ,Transc81_78 ,Transc81_79 ,Transc81_80 ,Transc81_81 ,

256==>[91, 126, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142, 144, 145, 146, 147, 149, 150, 151]
Variable Names ==> Five_Points_repet ,Transc_R_15 ,Transc_R_20 ,Transc_R_21 ,Transc_R_22 ,Transc_R_23 ,Transc_R_24 ,Transc_R_25 ,Transc_R_26 ,Transc_R_27 ,Transc_R_28 ,Transc_R_29 ,Transc_R_30 ,Transc_R_31 ,Transc_R_33 ,Transc_R_34 ,Transc_R_35 ,Transc_R_36 ,Transc_R_38 ,Transc_R_39 ,Transc_R_40 ,

484==>[93, 94, 95, 96, 97, 98, 99]
Variable Names ==> RAVLT_LA_1 ,RAVLT_LA_2 ,RAVLT_LA_3 ,RAVLT_LA_4 ,RAVLT_LA_5 ,RAVLT_LB_1 ,RAVLT_LA_6 ,

390==>[100]
Variable Names ==> RAVLT_LA_7 ,

391==>[101]
Variable Names ==> RAVLT_Reconhec ,

191==>[106, 107, 108, 109]
Variable Names ==> SRT_mean ,SRT_sd ,SRT_min ,SRT_max ,

257==>[112, 113, 114, 116, 118, 119, 121, 122, 123, 130]
Variable Names ==> Transc_R_1 ,Transc_R_2 ,Transc_R_3 ,Transc_R_5 ,Transc_R_7 ,Transc_R_8 ,Transc_R_10 ,Transc_R_11 ,Transc_R_12 ,Transc_R_19 ,

386==>[115]
Variable Names ==> Transc_R_4 ,

387==>[117]
Variable Names ==> Transc_R_6 ,

388==>[120]
Variable Names ==> Transc_R_9 ,

258==>[125, 143, 148, 758]
Variable Names ==> Transc_R_14 ,Transc_R_32 ,Transc_R_37 ,Rey_rec2_12 ,

253==>[129, 518]
Variable Names ==> Transc_R_18 ,MAQ_WC_02 ,

392==>[152]
Variable Names ==> Transc81_01_answ ,

393==>[153]
Variable Names ==> Transc81_02_answ ,

254==>[154]
Variable Names ==> Transc81_03_answ ,

209==>[155, 157, 158, 159, 461, 480]
Variable Names ==> Transc81_04_answ ,Transc81_06_answ ,Transc81_07_answ Transc81_08_answ ,CB_street ,CB_street_score ,

210==>[156]
Variable Names ==> Transc81_05_answ ,

259==>[160, 1066, 1067, 1068, 1069, 1070, 1071, 1072, 1073, 1074, 1075, 1076,

1077, 1078, 1079, 1080, 1081, 1082, 1083, 1084, 1085, 1086, 1087, 1088, 1089, 1090, 1091, 1092, 1093, 1094, 1095, 1096, 1097, 1098, 1099, 1100, 1101, 1102, 1103, 1104, 1105]
Variable Names ==> Transc81_09_answ ,Transc_1 ,Transc_2 ,Transc_3 ,Transc_4 ,Transc_5 ,Transc_6 ,Transc_7 ,Transc_8 ,Transc_9 ,Transc_10 ,Transc_11 ,Transc_12 ,Transc_13 ,Transc_14 ,Transc_15 ,Transc_16 ,Transc_17 ,Transc_18 ,Transc_19 ,Transc_20 ,Transc_21 ,Transc_22 ,Transc_23 ,Transc_24 ,Transc_25 ,Transc_26 ,Transc_27 ,Transc_28 ,Transc_29 ,Transc_30 ,Transc_31 ,Transc_32 ,Transc_33 ,Transc_34 ,Transc_35 ,Transc_36 ,Transc_37 ,Transc_38 ,Transc_39 ,Transc_40 ,

180==>[169]
Variable Names ==> Transc81_18_answ ,

179==>[170, 945]
Variable Names ==> Transc81_19_answ ,
Num_Line_Paper_Ajust_Logaritmic ,

207==>[171, 172, 173, 174, 175, 176, 177, 178, 201, 202, 203, 204, 205, 206, 207, 208, 209, 210, 211, 212, 213, 214, 215, 216, 217, 218, 219, 220, 221, 222, 223, 224, 225, 226, 227, 228, 229, 230, 231, 232, 808]
Variable Names ==> Transc81_20_answ ,Transc81_21_answ ,Transc81_22_answ ,Transc81_23_answ ,Transc81_24_answ ,Transc81_25_answ ,Transc81_26_answ ,Transc81_27_answ ,Transc81_50_answ ,Transc81_51_answ ,Transc81_52_answ ,Transc81_53_answ ,Transc81_54_answ ,Transc81_55_answ ,Transc81_56_answ ,Transc81_57_answ ,Transc81_58_answ ,Transc81_59_answ ,Transc81_60_answ ,Transc81_61_answ ,Transc81_62_answ ,Transc81_63_answ ,Transc81_64_answ ,Transc81_65_answ ,Transc81_66_answ ,Transc81_67_answ ,Transc81_68_answ ,Transc81_69_answ ,Transc81_70_answ ,Transc81_71_answ ,Transc81_72_answ ,Transc81_73_answ ,Transc81_74_answ ,Transc81_75_answ ,Transc81_76_answ ,Transc81_77_answ ,Transc81_78_answ ,Transc81_79_answ ,Transc81_80_answ ,Transc81_81_answ ,Banuca4_SS_8_resp

206==>[179, 180, 181, 182, 183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194, 195, 196, 197, 198, 199, 200]
Variable Names ==> Transc81_28_answ ,Transc81_29_answ ,Transc81_30_answ ,Transc81_31_answ ,Transc81_32_answ ,Transc81_33_answ ,Transc81_34_answ ,Transc81_35_answ ,Transc81_36_answ ,Transc81_37_answ ,Transc81_38_answ ,Transc81_39_answ ,Transc81_40_answ ,Transc81_41_answ ,Transc81_42_answ ,Transc81_43_answ ,Transc81_44_answ ,Transc81_45_answ ,Transc81_46_answ ,Transc81_47_answ ,Transc81_48_answ ,
Transc81_49_answ ,

394==>[233]
Variable Names ==> NumRead_1 ,

395==>[234]
Variable Names ==> NumRead_2 ,

396==>[235]
Variable Names ==> NumRead_3 ,

397==>[236]
Variable Names ==> NumRead_4 ,

90==>[237, 238, 244, 265, 266, 302]
Variable Names ==> NumRead_5 ,NumRead_6 ,NumRead_12 ,NumRead_R_5 ,NumRead_R_6 ,Add_S_03_answ ,

107==>[239, 240, 242, 243, 267, 268, 270, 271]
Variable Names ==> NumRead_7 ,NumRead_8 ,NumRead_10 ,NumRead_11 ,NumRead_R_7 ,NumRead_R_8 ,NumRead_R_10 ,NumRead_R_11 ,

398==>[241]
Variable Names ==> NumRead_9 ,

106==>[245, 246, 247, 250, 273, 274]
Variable Names ==> NumRead_13 ,NumRead_14 ,NumRead_15 ,NumRead_18 ,NumRead_R_13 ,NumRead_R_14 ,

66==>[248, 256, 258, 259, 260]
Variable Names ==> NumRead_16 ,NumRead_24 ,NumRead_26 ,NumRead_27 ,NumRead_28 ,

105==>[249, 251, 253, 254]
Variable Names ==> NumRead_17 ,NumRead_19 ,NumRead_21 ,NumRead_22 ,

65==>[252, 255, 257]
Variable Names ==> NumRead_20 ,NumRead_23 ,NumRead_25 ,

399==>[261]
Variable Names ==> NumRead_R_1 ,

400==>[262]
Variable Names ==> NumRead_R_2 ,

401==>[263]
Variable Names ==> NumRead_R_3 ,

402==>[264]
Variable Names ==> NumRead_R_4 ,

403==>[269]
Variable Names ==> NumRead_R_9 ,

186==>[272, 304]
Variable Names ==> NumRead_R_12 ,Add_S_05_answ ,

99==>[275]
Variable Names ==> NumRead_R_15 ,

103==>[276]
Variable Names ==> NumRead_R_17 ,

104==>[277]
Variable Names ==> NumRead_R_18 ,

182==>[278, 281]
Variable Names ==> NumRead_R_19 ,NumRead_R_22 ,

96==>[279, 282, 284]
Variable Names ==> NumRead_R_20 ,NumRead_R_23 ,NumRead_R_25 ,

181==>[280]
Variable Names ==> NumRead_R_21 ,

87==>[283, 285]
Variable Names ==> NumRead_R_24 ,NumRead_R_26 ,

101==>[286]
Variable Names ==> NumRead_R_27 ,

102==>[287]
Variable Names ==> NumRead_R_28 ,

40==>[288, 291, 1007, 1008, 1009, 1010, 1011, 1012, 1021, 1022, 1024]
Variable Names ==> Add_S_01 ,Add_S_04 ,Corsi_F_1_1 ,Corsi_F_1_2 ,Corsi_F_2_1 ,Corsi_F_2_2 ,Corsi_F_3_1 ,Corsi_F_3_2 ,Corsi_B_1_1 ,Corsi_B_1_2 ,Corsi_B_2_2 ,

50==>[289, 305]
Variable Names ==> Add_S_02 ,Add_S_06_answ ,

53==>[290, 292, 293, 294, 306]
Variable Names ==> Add_S_03 ,Add_S_05 ,Add_S_06 ,Add_S_07 ,Add_S_07_answ ,

56==>[295, 296, 297, 298, 299, 307, 308, 310, 336]
Variable Names ==> Add_S_08 ,Add_S_09 ,Add_S_10 ,Add_S_11 ,Add_S_12 ,Add_S_08_answ ,Add_S_09_answ ,Add_S_11_answ ,Add_C_10_answ ,

187==>[300]
Variable Names ==> Add_S_01_answ ,

98==>[301]
Variable Names ==> Add_S_02_answ ,

51==>[303, 313, 328, 330]
Variable Names ==> Add_S_04_answ ,Add_C_02 ,Add_C_02_answ ,Add_C_04_answ ,

85==>[309]
Variable Names ==> Add_S_10_answ ,

150==>[311, 390]
Variable Names ==> Add_S_12_answ ,Sub_C_10_answ ,

39==>[312, 327]
Variable Names ==> Add_C_01 ,Add_C_01_answ ,

58==>[314]
Variable Names ==> Add_C_03 ,

57==>[315, 317, 427]
Variable Names ==> Add_C_04 ,Add_C_06 ,Prob_04 ,

55==>[316, 331]
Variable Names ==> Add_C_05 ,Add_C_05_answ ,

438==>[318, 319, 321]
Variable Names ==> Add_C_07 ,Add_C_08 ,Add_C_10 ,

156==>[320, 322, 335, 337, 352, 353, 369, 384, 404, 406]
Variable Names ==> Add_C_09 ,Add_C_11 ,Add_C_09_answ ,Add_C_11_answ ,Sub_S_11 ,Sub_S_12 ,Sub_C_04 ,Sub_C_04_answ ,Mul_S_09_answ ,Mul_S_11_answ ,

143==>[323, 324, 325, 326, 370, 371, 373, 374]
Variable Names ==> Add_C_12 ,Add_C_13 ,Add_C_14 ,Add_C_15 ,Sub_C_05 ,Sub_C_06 ,Sub_C_08 ,Sub_C_09 ,

94==>[329]
Variable Names ==> Add_C_03_answ ,

190==>[332]
Variable Names ==> Add_C_06_answ ,

418==>[334, 874]
Variable Names ==> Add_C_08_answ ,Banuca8_CM_4_resp ,

60==>[342, 354]
Variable Names ==> Sub_S_01 ,Sub_S_01_answ ,

59==>[343, 344, 345]
Variable Names ==> Sub_S_02 ,Sub_S_03 ,Sub_S_04 ,

61==>[346, 347, 348, 359]
Variable Names ==> Sub_S_05 ,Sub_S_06 ,Sub_S_07 ,Sub_S_06_answ ,

154==>[349, 361]
Variable Names ==> Sub_S_08 ,Sub_S_08_answ ,

155==>[350, 351, 362, 363, 364, 365]
Variable Names ==> Sub_S_09 ,Sub_S_10 ,Sub_S_09_answ ,Sub_S_10_answ , Sub_S_11_answ ,Sub_S_12_answ ,

97==>[355, 357]
Variable Names ==> Sub_S_02_answ ,Sub_S_04_answ ,

108==>[356]
Variable Names ==> Sub_S_03_answ ,

95==>[358]
Variable Names ==> Sub_S_05_answ ,

109==>[360]
Variable Names ==> Sub_S_07_answ ,

141==>[366, 367, 368]
Variable Names ==> Sub_C_01 ,Sub_C_02 ,Sub_C_03 ,

142==>[376, 377, 378, 379, 380]
Variable Names ==> Sub_C_11 ,Sub_C_12 ,Sub_C_13 ,Sub_C_14 ,Sub_C_15 ,

110==>[381]
Variable Names ==> Sub_C_01_answ ,

93==>[382, 383]
Variable Names ==> Sub_C_02_answ ,Sub_C_03_answ ,

75==>[392, 700, 701, 711, 714, 724, 726, 728]
Variable Names ==> Sub_C_12_answ ,Orient_8 ,Orient_9 ,Fgnosia_RH_7 ,Fgnosia_RH_10 ,Fgnosia_LH_8 ,Fgnosia_LH_10 ,Fgnosia_LH_12 ,

183==>[397, 402, 898]
Variable Names ==> Mul_S_02_answ ,Mul_S_07_answ ,Banuca9_RA_3_resp ,

41==>[398]
Variable Names ==> Mul_S_03_answ ,

86==>[400]
Variable Names ==> Mul_S_05_answ ,

151==>[401, 403, 405, 408]
Variable Names ==> Mul_S_06_answ ,Mul_S_08_answ ,Mul_S_10_answ ,Mul_S_13_answ

,

432==>[411]
Variable Names ==> Mul_C_01_answ ,

433==>[412]
Variable Names ==> Mul_C_02_answ ,

84==>[413, 414]
Variable Names ==> Mul_C_03_answ ,Mul_C_04_answ ,

416==>[415, 417, 418, 423]
Variable Names ==> Mul_C_05_answ ,Mul_C_07_answ ,Mul_C_08_answ ,Mul_C_13_answ
,

211==>[419, 420, 422]
Variable Names ==> Mul_C_09_answ ,Mul_C_10_answ ,Mul_C_12_answ ,

195==>[421, 866]
Variable Names ==> Mul_C_11_answ ,Banuca8_CM_6 ,

74==>[424, 436]
Variable Names ==> Prob_01 ,Prob_R_1 ,

72==>[425]
Variable Names ==> Prob_02 ,

71==>[426, 438]
Variable Names ==> Prob_03 ,Prob_R_3 ,

70==>[428, 429, 440, 441]
Variable Names ==> Prob_05 ,Prob_06 ,Prob_R_5 ,Prob_R_6 ,

73==>[430, 442]
Variable Names ==> Prob_07 ,Prob_R_7 ,

431==>[431, 443]
Variable Names ==> Prob_08 ,Prob_R_8 ,

430==>[432, 444]
Variable Names ==> Prob_09 ,Prob_R_9 ,

69==>[433, 434, 446]
Variable Names ==> Prob_10 ,Prob_11 ,Prob_R_11 ,

68==>[435, 447]
Variable Names ==> Prob_12 ,Prob_R_12 ,

185==>[437]
Variable Names ==> Prob_R_2 ,

42==>[439]
Variable Names ==> Prob_R_4 ,

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265==>[448, 467]
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268==>[449, 456, 468, 475]
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282==>[450, 469]
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422==>[451, 470]
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419==>[452, 471]
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266==>[453, 472]
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269==>[454, 460, 463, 473, 479]
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270==>[455, 474]
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421==>[457, 476]
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272==>[458, 477, 504, 735]
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420==>[459, 478]
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423==>[462, 481, 503]
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82==>[464]
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216==>[465]
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214==>[466, 997, 998]

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447==>[482, 493]

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451==>[483, 494]

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260==>[484, 495]

Variable Names ==> OV_CB_bath ,OV_CB_bath_score ,

448==>[485, 496]

Variable Names ==> OV_CB_car ,OV_CB_car_score ,

449==>[486, 497]

Variable Names ==> OV_CB_hm ,OV_CB_hm_score ,

262==>[487, 1000]

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446==>[488, 499]

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274==>[489]

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452==>[490, 501]

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273==>[491, 502]

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280==>[492, 522]

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263==>[498]

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167==>[509]

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202==>[511, 512]

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284==>[517]

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164==>[519, 749, 759]

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281==>[525]

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24==>[529, 530, 531, 670, 680]

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22==>[545, 678]

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18==>[549, 667]

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32==>[550, 555]

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166==>[566, 567, 568, 730, 732]

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174==>[569, 733]

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176==>[571]
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173==>[572, 576]
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175==>[573, 574]
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159==>[575, 966]
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172==>[578, 579, 580]
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161==>[582, 746]
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383==>[583]
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493==>[584, 585, 586, 587, 588, 589, 590, 591, 592, 594, 595, 596, 597, 598, 600, 601, 602, 603, 604, 605, 606]
Variable Names ==> Est_median_2 ,Est_median_3 ,Est_median_4 ,Est_median_5 ,Est_median_10 ,Est_median_16 ,
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385==>[599]
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377==>[609]
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378==>[610]
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379==>[611]
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380==>[612]
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374==>[613]
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366==>[614]
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359==>[615]
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360==>[620]
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356==>[623]
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9==>[624, 626, 635, 659]
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10==>[625, 641, 647]
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8==>[627, 660]
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6==>[629, 636]
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4==>[630, 632, 638, 649, 652]
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25==>[633, 653, 663, 666, 685, 686]
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13==>[637, 643, 644, 648, 650, 661, 665, 679]
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17==>[656, 692]
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23==>[658, 662, 683]
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21==>[675, 682, 689]
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14==>[684, 688, 690]
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358==>[696]
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361==>[697]
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362==>[698]
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363==>[699]

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425==>[702, 788]

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364==>[705]

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365==>[706]

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367==>[707]

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368==>[708]

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369==>[709]

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355==>[717]

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353==>[718]

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354==>[719]

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331==>[720]

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333==>[722]

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335==>[725]
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336==>[727]
Variable Names ==> Fgnosia_LH_11 ,

168==>[729]
Variable Names ==> Rey_rec1_1 ,

197==>[731, 985, 986, 987]
Variable Names ==> Rey_rec1_3 ,FT_E_1 ,FT_E_2 ,FT_LH_mean_final ,

162==>[734]
Variable Names ==> Rey_rec1_6 ,

171==>[736]
Variable Names ==> Rey_rec1_8 ,

203==>[737]
Variable Names ==> Rey_rec1_9 ,

44==>[738, 1037, 1038, 1039, 1040, 1041, 1042, 1053, 1054, 1055, 1056]
Variable Names ==> Rey_rec1_10 ,Dspan_F_1_1 ,Dspan_F_1_2 ,Dspan_F_2_1 ,Dspan_F_2_2 ,Dspan_F_3_1 ,Dspan_F_3_2 ,Dspan_B_1_1 ,Dspan_B_1_2 ,Dspan_B_2_1 ,Dspan_B_2_2 ,

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170==>[744, 762]
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158==>[747]
Variable Names ==> Rey_rec2_1 ,

137==>[750, 751, 873, 895]
Variable Names ==> Rey_rec2_4 ,Rey_rec2_5 ,Banuca8_CM_3_resp ,Banuca9_RA_15 ,

485==>[752, 876]
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91==>[754]
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264==>[755, 995, 996]
Variable Names ==> Rey_rec2_9 ,NM_index_nose_eyes_open ,NM_index_nose_eyes_close ,

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Variable Names ==> Rey_rec2_11 ,

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246==>[763, 1264]
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Variable Names ==> Banuca1_CP_1 ,

338==>[766]
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339==>[767]
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340==>[768]
Variable Names ==> Banuca1_CP_4 ,

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343==>[771]
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344==>[772]
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345==>[774]
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139==>[775, 776, 777, 783, 784, 785, 804, 851, 859]
Variable Names ==> Banuca2_AS_5 ,Banuca2_AS_6 ,Banuca2_AS_7 ,Banuca2_AS_5_resp ,Banuca2_AS_6_resp ,Banuca2_AS_7_resp ,Banuca4_SS_4_resp ,

Banuca7_RN_7 ,Banuca7_RN_7_resp ,

417==>[778, 850, 858, 865]
Variable Names ==> Banuca2_AS_8 ,Banuca7_RN_6 ,Banuca7_RN_6_resp ,Banuca8_CM_5 ,

346==>[779]
Variable Names ==> Banuca2_AS_1_resp ,

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136==>[781, 789, 790, 791, 792, 797, 798, 799, 805, 806, 807, 839, 842, 868, 869, 890, 905]
Variable Names ==> Banuca2_AS_3_resp ,Banuca3_C_3 ,Banuca3_C_4 ,Banuca3_C_5 ,Banuca3_C_6 ,Banuca4_SS_5 ,Banuca4_SS_6 ,
Banuca4_SS_7 ,Banuca4_SS_5_resp ,Banuca4_SS_6_resp ,
Banuca4_SS_7_resp ,Banuca6_CN_5_resp ,Banuca6_CN_8_resp ,
Banuca8_CM_8 ,Banuca8_CM_9 ,Banuca9_RA_10 ,Banuca9_RA_10_resp ,

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352==>[795]
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320==>[801]
Variable Names ==> Banuca4_SS_1_resp ,

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317==>[803]
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318==>[809]
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321==>[810]
Variable Names ==> Banuca5_LN_2 ,

322==>[811]
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Variable Names ==> Banuca5_LN_4 ,

324==>[813]
Variable Names ==> Banuca5_LN_5 ,

138==>[815, 833, 843, 852, 860, 886, 901]
Variable Names ==> Banuca5_LN_7 ,Banuca6_CN_9 ,Banuca6_CN_9_resp ,Banuca7_RN_8 ,Banuca7_RN_8_resp ,
Banuca9_RA_6 ,Banuca9_RA_6_resp ,

325==>[816]
Variable Names ==> Banuca5_LN_8 ,

326==>[817]
Variable Names ==> Banuca5_LN_1_resp ,

327==>[818]
Variable Names ==> Banuca5_LN_2_resp ,

328==>[819]
Variable Names ==> Banuca5_LN_3_resp ,

329==>[820]
Variable Names ==> Banuca5_LN_4_resp ,

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315==>[825]
Variable Names ==> Banuca6_CN_1 ,

311==>[827]
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Variable Names ==> Banuca6_CN_4 ,Banuca6_CN_4_resp ,

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295==>[835]
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296==>[836]
Variable Names ==> Banuca6_CN_2_resp ,

297==>[837]
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298==>[840]
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299==>[845]
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300==>[846]
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301==>[847]
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302==>[848]
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303==>[849]
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292==>[853]
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293==>[854]
Variable Names ==> Banuca7_RN_2_resp ,

294==>[855]
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304==>[856]
Variable Names ==> Banuca7_RN_4_resp ,

285==>[857]
Variable Names ==> Banuca7_RN_5_resp ,

30==>[864, 892, 907]
Variable Names ==> Banuca8_CM_4 ,Banuca9_RA_12 ,Banuca9_RA_12_resp ,

483==>[867, 889]
Variable Names ==> Banuca8_CM_7 ,Banuca9_RA_9 ,

286==>[870]
Variable Names ==> Banuca8_CM_10 ,

498==>[877, 988]
Variable Names ==> Banuca8_CM_7_resp ,NM_Fgnosia_RH_1 ,

47==>[878, 880]
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287==>[881]
Variable Names ==> Banuca9_RA_1 ,

288==>[887]
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290==>[896]
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291==>[902]
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305==>[917]
Variable Names ==> Fgnosias_RLH_visivel ,

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62==>[920, 926, 931, 942]
Variable Names ==>
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80==>[921]
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63==>[922, 929, 930, 932, 933, 934, 937, 938, 939, 941]
Variable Names ==> Num_Line_Paper_23 ,Num_Line_Paper_12 ,Num_Line_Paper_25
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,Num_Line_Paper_43 ,Num_Line_Paper_29 ,Num_Line_Paper_33 ,

79==>[923, 927, 928, 935]
Variable Names ==>
Num_Line_Paper_84 ,Num_Line_Paper_81 ,Num_Line_Paper_90 ,Num_Line_Paper_96
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437==>[924, 925]
Variable Names ==> Num_Line_Paper_61 ,Num_Line_Paper_64 ,

64==>[936, 940]
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306==>[946]
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307==>[947]
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308==>[948]
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220==>[951]
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276==>[955]
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145==>[960, 961, 969, 970]
Variable Names ==> mult_comp_med7 ,mult_comp_med8 ,mult_comp_dp7 ,mult_comp_dp8

196==>[982, 983, 984]
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213==>[989, 990]
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313==>[991]
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200==>[992]
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497==>[999, 1065]
Variable Names ==> Consistencia_Lat_H ,hand_preferencia ,

450==>[1001, 1002]
Variable Names ==> SES_juntado ,SES_justado_nominal ,

455==>[1003]
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415==>[1004]
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194==>[1005]
Variable Names ==> wisc_reduzido_final ,

429==>[1006]
Variable Names ==> preferencia_manual ,

36==>[1013, 1014, 1015, 1016]
Variable Names ==> Corsi_F_4_1 ,Corsi_F_4_2 ,Corsi_F_5_1 ,Corsi_F_5_2 ,

490==>[1017, 1018]
Variable Names ==> Corsi_F_6_1 ,Corsi_F_6_2 ,

486==>[1019, 1020]
Variable Names ==> Corsi_F_7_1 ,Corsi_F_7_2 ,

38==>[1023, 1025, 1026, 1027, 1028]
Variable Names ==> Corsi_B_2_1 ,Corsi_B_3_1 ,Corsi_B_3_2 ,Corsi_B_4_1 ,Corsi_B_4_2

492==>[1029, 1030]
Variable Names ==> Corsi_B_5_1 ,Corsi_B_5_2 ,

491==>[1031, 1032]
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489==>[1033, 1034, 1035, 1036]
Variable Names ==> Corsi_B_7_1 ,Corsi_B_7_2 ,Corsi_B_8_1 ,Corsi_B_8_2 ,

43==>[1043, 1044, 1045, 1046]
Variable Names ==> Dspan_F_4_1 ,Dspan_F_4_2 ,Dspan_F_5_1 ,Dspan_F_5_2 ,

435==>[1047, 1048, 1049, 1050]
Variable Names ==> Dspan_F_6_1 ,Dspan_F_6_2 ,Dspan_F_7_1 ,Dspan_F_7_2 ,

434==>[1051, 1052]
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35==>[1057, 1058, 1059, 1060]
Variable Names ==> Dspan_B_3_1 ,Dspan_B_3_2 ,Dspan_B_4_1 ,Dspan_B_4_2

488==>[1061, 1062]
Variable Names ==> Dspan_B_5_1 ,Dspan_B_5_2 ,

487==>[1063, 1064]
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46==>[1187, 1188, 1189, 1190, 1191, 1192, 1202, 1203]
Variable Names ==>
Mul_S_01 ,Mul_S_02 ,Mul_S_03 ,Mul_S_04 ,Mul_S_05 ,Mul_S_06 ,Mul_C_01 ,Mul_C_02 ,

45==>[1193, 1194, 1195, 1196, 1197, 1198, 1199, 1200, 1201]
Variable Names ==> Mul_S_07 ,Mul_S_08 ,Mul_S_09 ,Mul_S_10 ,Mul_S_11 ,Mul_S_12 ,Mul_S_13 ,Mul_S_14 ,Mul_S_15 ,

49==>[1204, 1205, 1206, 1207]
Variable Names ==> Mul_C_03 ,Mul_C_04 ,Mul_C_05 ,Mul_C_06 ,

48==>[1208, 1209, 1210, 1211, 1212, 1213, 1214]
Variable Names ==> Mul_C_07 ,Mul_C_08 ,Mul_C_09 ,Mul_C_10 ,Mul_C_11 ,Mul_C_12 ,Mul_C_13 ,

462==>[1215]
Variable Names ==> SNAP_1 ,

461==>[1216]
Variable Names ==> SNAP_2 ,

464==>[1217]
Variable Names ==> SNAP_3 ,

453==>[1218]
Variable Names ==> SNAP_4 ,

454==>[1219]
Variable Names ==> SNAP_5 ,

465==>[1220]
Variable Names ==> SNAP_6 ,

458==>[1221]
Variable Names ==> SNAP_7 ,

463==>[1222]
Variable Names ==> SNAP_8 ,

459==>[1223]
Variable Names ==> SNAP_9 ,

460==>[1224]
Variable Names ==> SNAP_10 ,

476==>[1225]
Variable Names ==> SNAP_11 ,

477==>[1226]
Variable Names ==> SNAP_12 ,

472==>[1227]
Variable Names ==> SNAP_13 ,

473==>[1228]
Variable Names ==> SNAP_14 ,

480==>[1229]
Variable Names ==> SNAP_15 ,

478==>[1230]
Variable Names ==> SNAP_16 ,

479==>[1231]
Variable Names ==> SNAP_17 ,

474==>[1232]
Variable Names ==> SNAP_18 ,

475==>[1233]
Variable Names ==> SNAP_19 ,

466==>[1234]
Variable Names ==> SNAP_20 ,

471==>[1235]
Variable Names ==> SNAP_21 ,

470==>[1236]
Variable Names ==> SNAP_22 ,

468==>[1237]
Variable Names ==> SNAP_23 ,

467==>[1238]
Variable Names ==> SNAP_24 ,

261==>[1239]
Variable Names ==> SNAP_25 ,

469==>[1240]
Variable Names ==> SNAP_26 ,

230==>[1241, 1311]
Variable Names ==> CBCL_1 ,CBCL_64 ,

250==>[1242, 1246, 1255, 1256, 1270, 1280, 1303, 1304, 1306, 1307, 1314, 1317, 1319, 1320, 1328, 1329, 1343, 1344, 1345, 1346, 1348, 1352, 1353, 1354, 1355, 1357, 1360]

Variable Names ==> CBCL_2 ,CBCL_6 ,CBCL_15 ,CBCL_16 ,CBCL_30 ,CBCL_40 ,CBCL_56_h ,CBCL_57 ,CBCL_59 ,CBCL_60 ,CBCL_67 ,CBCL_70 ,CBCL_72 ,CBCL_73 ,CBCL_81 ,CBCL_82 ,CBCL_96 ,CBCL_97 ,CBCL_98 ,CBCL_99 ,CBCL_101 ,CBCL_105 ,CBCL_106 ,CBCL_107 ,CBCL_108 ,CBCL_110 ,CBCL_113 ,

227==>[1243, 1285, 1333, 1334, 1335, 1342]
Variable Names ==> CBCL_3 ,CBCL_45 ,CBCL_86 ,CBCL_87 ,CBCL_88 ,CBCL_95

229==>[1244, 1248, 1308, 1325]
Variable Names ==> CBCL_4 ,CBCL_8 ,CBCL_61 ,CBCL_78 ,

235==>[1245, 1312, 1327, 1350]
Variable Names ==> CBCL_5 ,CBCL_65 ,CBCL_80 ,CBCL_103 ,

247==>[1247, 1321]
Variable Names ==> CBCL_7 ,CBCL_74 ,

245==>[1249, 1252, 1313, 1336]
Variable Names ==> CBCL_9 ,CBCL_12 ,CBCL_66 ,CBCL_89 ,

248==>[1250, 1315, 1340, 1351]
Variable Names ==> CBCL_10 ,CBCL_68 ,CBCL_93 ,CBCL_104 ,

238==>[1251, 1269, 1290]
Variable Names ==> CBCL_11 ,CBCL_29 ,CBCL_50 ,

222==>[1253, 1281]
Variable Names ==> CBCL_13 ,CBCL_41 ,

226==>[1254, 1356]
Variable Names ==> CBCL_14 ,CBCL_109 ,

244==>[1257, 1330]
Variable Names ==> CBCL_17 ,CBCL_83 ,

252==>[1258, 1286, 1331, 1332, 1338]
Variable Names ==> CBCL_18 ,CBCL_46 ,CBCL_84 ,CBCL_85 ,CBCL_91 ,

217==>[1259, 1267, 1273]
Variable Names ==> CBCL_19 ,CBCL_27 ,CBCL_33 ,

251==>[1260, 1261]
Variable Names ==> CBCL_20 ,CBCL_21 ,

225==>[1262, 1263, 1266, 1268, 1283]
Variable Names ==> CBCL_22 ,CBCL_23 ,CBCL_26 ,CBCL_28 ,CBCL_43 ,

236==>[1265, 1282, 1288, 1358]
Variable Names ==> CBCL_25 ,CBCL_42 ,CBCL_48 ,CBCL_111 ,

241==>[1271, 1272, 1292]
Variable Names ==> CBCL_31 ,CBCL_32 ,CBCL_52 ,

219==>[1274, 1275]
Variable Names ==> CBCL_34 ,CBCL_35 ,

223==>[1276, 1309]
Variable Names ==> CBCL_36 ,CBCL_62 ,

218==>[1277, 1278, 1279]
Variable Names ==> CBCL_37 ,CBCL_38 ,CBCL_39 ,

231==>[1284]
Variable Names ==> CBCL_44 ,

243==>[1287, 1339, 1359]
Variable Names ==> CBCL_47 ,CBCL_92 ,CBCL_112 ,

239==>[1289]
Variable Names ==> CBCL_49 ,

240==>[1293, 1294, 1295]
Variable Names ==> CBCL_53 ,CBCL_54 ,CBCL_55 ,

221==>[1305]
Variable Names ==> CBCL_58 ,

249==>[1310, 1324]
Variable Names ==> CBCL_63 ,CBCL_77 ,

233==>[1316, 1326]
Variable Names ==> CBCL_69 ,CBCL_79 ,

232==>[1318, 1322]
Variable Names ==> CBCL_71 ,CBCL_75 ,

242==>[1323, 1347]
Variable Names ==> CBCL_76 ,CBCL_100 ,

224==>[1337, 1341]
Variable Names ==> CBCL_90 ,CBCL_94 ,

234==>[1349]
Variable Names ==> CBCL_102 ,

121==>[1361, 1397, 1399]
Variable Names ==> TDE_Spell_name ,TDE_Arit_oral_2 ,TDE_Arit_1 ,

112==>[1362, 1363, 1364, 1365, 1366, 1371, 1372]
Variable Names ==> TDE_Spell_1 ,TDE_Spell_2 ,TDE_Spell_3 ,TDE_Spell_4

,TDE_Spell_5 ,TDE_Spell_10 ,TDE_Spell_11 ,

116==>[1367]
Variable Names ==> TDE_Spell_6 ,

115==>[1368, 1377]
Variable Names ==> TDE_Spell_7 ,TDE_Spell_16 ,

118==>[1369, 1385, 1392, 1394]
Variable Names ==> TDE_Spell_8 ,TDE_Spell_24 ,TDE_Spell_31 ,TDE_Spell_33 ,

119==>[1370, 1378, 1379, 1388]
Variable Names ==> TDE_Spell_9 ,TDE_Spell_17 ,TDE_Spell_18 ,TDE_Spell_27 ,

120==>[1373, 1375, 1376]
Variable Names ==> TDE_Spell_12 ,TDE_Spell_14 ,TDE_Spell_15 ,

111==>[1374, 1381, 1383]
Variable Names ==> TDE_Spell_13 ,TDE_Spell_20 ,TDE_Spell_22 ,

114==>[1380, 1387, 1390, 1395]
Variable Names ==> TDE_Spell_19 ,TDE_Spell_26 ,TDE_Spell_29 ,TDE_Spell_34

113==>[1382, 1384, 1386, 1391]
Variable Names ==> TDE_Spell_21 ,TDE_Spell_23 ,TDE_Spell_25 ,TDE_Spell_30

117==>[1389, 1393]
Variable Names ==> TDE_Spell_28 ,TDE_Spell_32 ,

129==>[1396, 1408, 1410]
Variable Names ==> TDE_Arit_oral_1 ,TDE_Arit_10 ,TDE_Arit_12 ,

132==>[1398]
Variable Names ==> TDE_Arit_oral_3 ,

133==>[1400, 1402]
Variable Names ==> TDE_Arit_2 ,TDE_Arit_4 ,

122==>[1401]
Variable Names ==> TDE_Arit_3 ,

131==>[1403, 1404]
Variable Names ==> TDE_Arit_5 ,TDE_Arit_6 ,

130==>[1405, 1406]
Variable Names ==> TDE_Arit_7 ,TDE_Arit_8 ,

126==>[1407, 1409, 1411]
Variable Names ==> TDE_Arit_9 ,TDE_Arit_11 ,TDE_Arit_13 ,

127==>[1412, 1414]

Variable Names ==> TDE_Arit_14 ,TDE_Arit_16 ,

125==>[1413, 1415]
Variable Names ==> TDE_Arit_15 ,TDE_Arit_17 ,

128==>[1416, 1417, 1421]
Variable Names ==> TDE_Arit_18 ,TDE_Arit_19 ,TDE_Arit_23 ,

123==>[1418, 1419, 1420, 1427, 1428, 1429, 1431]
Variable Names ==> TDE_Arit_20 ,TDE_Arit_21 ,TDE_Arit_22 ,TDE_Arit_29 ,TDE_Arit_30 ,TDE_Arit_31 ,TDE_Arit_33 ,

124==>[1422, 1423, 1424, 1425, 1430, 1432, 1433]
Variable Names ==> TDE_Arit_24 ,TDE_Arit_25 ,TDE_Arit_26 ,TDE_Arit_27 ,TDE_Arit_32 ,TDE_Arit_34 ,TDE_Arit_35 ,

134==>[1426]
Variable Names ==> TDE_Arit_28 ,

135==>[1494, 1495, 1496, 1497, 1498, 1499, 1500, 1501, 1502, 1503, 1504, 1505, 1506, 1507, 1508, 1509, 1510, 1511, 1512, 1513, 1514, 1515, 1516, 1517, 1518, 1519, 1520, 1521, 1522, 1523, 1524, 1525, 1526, 1527, 1528, 1529]
Variable Names ==> Raven_A_1 ,Raven_A_2 ,Raven_A_3 ,Raven_A_4 ,Raven_A_5 ,Raven_A_6 ,Raven_A_7 ,Raven_A_8 ,Raven_A_9 ,Raven_A_10 ,Raven_A_11 ,Raven_A_12 ,Raven_AB_1 ,Raven_AB_2 ,Raven_AB_3 ,Raven_AB_4 ,Raven_AB_5 ,Raven_AB_6 ,Raven_AB_7 ,Raven_AB_8 ,Raven_AB_9 ,Raven_AB_10 ,Raven_AB_11 ,Raven_AB_12 ,Raven_B_1 ,Raven_B_2 ,Raven_B_3 ,Raven_B_4 ,Raven_B_5 ,Raven_B_6 ,Raven_B_7 ,Raven_B_8 ,Raven_B_9 ,Raven_B_10 ,Raven_B_11 ,Raven_B_12 ,

501==>[1530, 1531, 1532, 1533, 1534, 1535, 1536, 1537, 1538, 1539, 1540, 1542, 1543, 1544, 1545, 1546, 1548, 1549, 1550, 1555, 1558, 1559, 1560, 1561, 1563, 1564, 1568]
Variable Names ==> NM_Lat_H_1 ,NM_Lat_H_2 ,NM_Lat_H_3 ,NM_Lat_H_result ,NM_Lat_Y_1 ,NM_Lat_Y_2 ,NM_Lat_Y_3 ,NM_Lat_Y_result ,NM_Lat_F_result ,NM_Moeda_D ,NM_Moeda_E ,NM_Pantonima2 ,NM_Pantonima3 ,NM_Pantonima4 ,NM_Pantonima5 ,NM_Pantonima6 ,InstrucesConflitantes ,GonoGo ,index_index ,Marcha ,NM_Romberg ,NM_Reacao_eq_frente ,NM_Reacao_eq_tras ,NM_Reacao_eq_lat ,NM_Marcha_ponta_pe ,NM_Marcha_calcanhar ,NM_Coordenacao ,

442==>[1541]
Variable Names ==> NM_Pantonima1 ,

499==>[1547, 1552, 1567]
Variable Names ==> SequenciaMotora ,Disdiadococinesia ,NM_Polichinelo ,

443==>[1551]

Variable Names ==> Oponencia ,

495==>[1553]

Variable Names ==> Oseretski ,

496==>[1554]

Variable Names ==> Impersistencia_motora ,

494==>[1556, 1557, 1565]

Variable Names ==> NM_Tanden_frente ,NM_Tanden_tras ,NM_Apoio_unipodal ,

500==>[1562, 1566]

Variable Names ==> NM_Corrida ,NM_Salto_palmas ,

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Leader variables 0==>Age_months
3==>RavenNovo_junto_Adulto
5==>ParaCOM_QI
21==>Arranj_fig_Pond
31==>Nine_RH_mean
35==>Nine_Relative_handedness
37==>Fluenc_Arit_CalcFeitos
38==>Fluenc_Arit_CalcPulados
42==>Nscreener_Simb_Made
46==>Reading_Fluency_Time
47==>Reading_Fluency_LP
56==>Multidigits_T_Adicao
60==>Warring_operacoes
63==>Repet_Pseudo_15
65==>Repet_Pseudo_40
66==>RAN_1
70==>RAN_1_erros
71==>RAN_2_erros
74==>CBCL_SomaticComplaints_SN
77==>Add_C_Time
81==>Mul_C_Time
84==>SNAP_Mean_ADHD_inattention
98==>RAVLT_LB_1
104==>Stroop_Vic_Incongr
252==>NumRead_20

269==>NumRead_R_9
294==>Add_S_07
318==>Add_C_07
336==>Add_C_10_answ
378==>Sub_C_13
399==>Mul_S_04_answ
404==>Mul_S_09_answ
411==>Mul_C_01_answ
424==>Prob_01
448==>CB_bath
451==>CB_computador
462==>CB_Father_educ
482==>OV_CB_tv
483==>OV_CB_radio
491==>OV_CB_iy
507==>MAQ_GM_03
512==>MAQ_EC_04
513==>MAQ_DC_01
534==>Pho_Elis_03
565==>Rey_copy_1
584==>Est_median_2
656==>TDE_Read_34
764==>Rey_rec2_18
765==>Banuca1_CP_1
778==>Banuca2_AS_8
892==>Banuca9_RA_12
922==>Num_Line_Paper_23
982==>FT_D_1
993==>NM_Fgnosia_LH_3
1007==>Corsi_F_1_1
1017==>Corsi_F_6_1
1021==>Corsi_F_8_1
1035==>Corsi_B_7_1
1070==>Transc_1
1237==>SNAP_19
1365==>TDE_Spell_name
1416==>TDE_Arit_14
1438==>LPI_Reg_01
1498==>Raven_A_1

List of cluster variables

47==>[0, 1, 2, 49, 50, 51, 52, 58, 106, 107, 108, 109, 319, 508, 711, 724, 726, 883, 951, 953]
Variable Names ==> Age_months ,Age_years ,Grade ,Five_Dig_Read_RT ,Five_Dig_Cout_RT ,Five_Dig_Choos_RT ,Five_Dig_Switch_RT ,Multidigits_T_Mult ,SRT_mean ,SRT_sd ,SRT_min ,SRT_max ,Add_C_08 ,MAQ_GM_04 ,Fgnosia_RH_7 ,Fgnosia_LH_8 ,Fgnosia_LH_10 ,Banuca9_RA_3 ,Span_PP_6 ,Span_PP_8 ,

57==>[3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 22, 23, 24, 25, 26, 28, 29, 641, 792, 1005]
Variable Names ==> RavenNovo_junto_Adulto ,Inteligencia_FINAL_juntos ,Vocab_PP_revisado ,Cubos_PP_revisado ,QI_T ,CV ,OP ,IMO_RD ,VP ,QI_V ,QI_E ,Semel_PP_Triagem ,Digitos_Pond ,Semelh_Pond ,Inform_Pond ,Compreen_Pon ,Compl_fig_Pond ,Armar_obj_Pond ,Racioc_Matric_Pon ,Conc_Fig_Pond ,Arit_Pond ,Seq_N_Let_Pon ,Codigos_Pond ,
Proc_Simb_Pond ,TDE_Read_19 ,Banuca3_C_6 ,wisc_reduzido_final ,

24==>[5, 36, 266, 268, 280, 303, 329, 396, 401, 402, 403, 410, 439, 523, 582, 782, 828, 838, 864, 898, 908, 912, 913, 915, 945]
Variable Names ==> ParaCOM_QI ,fracao_w ,NumRead_R_6 ,NumRead_R_8 ,NumRead_R_21 ,Add_S_04_answ ,Add_C_03_answ ,Mul_S_01_answ ,Mul_S_06_answ ,Mul_S_07_answ ,Mul_S_08_answ ,Mul_S_15_answ ,Prob_R_4 ,MAQ_MC_03 ,Rey_copy_18 ,Banuca2_AS_4_resp ,
Banuca6_CN_4 ,Banuca6_CN_4_resp ,Banuca8_CM_4 ,Banuca9_RA_3_resp,
Banuca9_RA_13_resp ,Fgnosia_RH_escondido ,Fgnosia_RH_dois_dedos ,Fgnosia_LH_escondido ,Num_Line_Paper_Ajust_Logaritmic ,

54==>[21, 27, 30, 59, 64, 92, 111, 248, 533, 543, 561, 562, 563, 577, 578, 607, 608, 609, 610, 611, 612, 613, 614, 615, 616, 617, 620, 622, 694, 695, 700, 701, 703, 704, 712, 713, 714, 715, 716, 719, 720, 721, 727, 728, 741, 742, 748, 751, 759, 760, 799, 833, 834, 841, 850, 889]
Variable Names ==> Arranj_fig_Pond ,Racioc_Palavras_Pond ,Cancel_Pond ,Warring_multiplicacao ,Supressao_Fon_30 ,Five_Points_erros ,Verbal_Fluency_An_Repetition ,NumRead_16 ,Pho_Elis_02 ,Pho_Elis_12 ,Five_Dig_Count_E ,Five_Dig_Choos_E ,Five_Dig_Switch_E ,Rey_copy_13 ,Rey_copy_14 ,Digits_error_1 ,Digits_error_2 ,Digits_error_3 ,Digits_error_4 ,Digits_error_6 ,Digits_error_7 ,Digits_error_8 ,Digits_error_9 ,Digits_arcsine_1 ,Digits_arcsine_2 ,Digits_arcsine_3 ,Digits_arcsine_7 ,Digits_arcsine_9 ,Orient_2 ,Orient_3 ,Orient_8 ,Orient_9 ,Orient_11 ,Orient_12 ,Fgnosia_RH_8 ,Fgnosia_RH_9 ,Fgnosia_RH_10 ,Fgnosia_RH_11 ,Fgnosia_RH_12 ,Fgnosia_LH_3 ,Fgnosia_LH_4 ,Fgnosia_LH_5 ,Fgnosia_LH_11 ,Fgnosia_LH_12 ,Rey_rec1_13

,Rey_rec1_14 ,Rey_rec2_2 ,Rey_rec2_5 ,Rey_rec2_13 ,Rey_rec2_14 ,Banuca4_SS_7 ,Banuca6_CN_9 ,Banuca6_CN_10 ,Banuca6_CN_7_resp ,Banuca7_RN_6 ,Banuca9_RA_9 ,

46==>[31, 32, 33, 34, 887]
Variable Names ==> Nine_RH_mean ,Nine_DH_mean ,Nine_LH_mean ,Nine_NDH_mean ,Banuca9_RA_7 ,

36==>[35, 110, 155, 304, 357, 386, 398, 437, 452, 453, 471, 472, 479, 480, 731, 749, 1003, 1004, 1555, 1558]
Variable Names ==> Nine_Relative_handedness ,wrsquared ,Transc81_04_answ ,Add_S_05_answ ,Sub_S_04_answ ,Sub_C_06_answ ,Mul_S_03_answ ,Prob_R_2 ,CB_dw ,CB_fridge ,CB_dw_score ,CB_fridge_score ,CB_water_score ,CB_street_score ,Rey_rec1_3 ,Rey_rec2_3 ,Sex ,School_type ,Oponencia ,Impersistencia_motora ,

49==>[37, 40, 41, 44, 45, 55, 82, 88, 102, 771, 772, 773, 775, 776, 777, 785, 786, 789, 790, 791, 793, 794, 795, 796, 797, 801, 802, 803, 804, 810, 811, 812, 813, 814, 815, 816, 823, 824, 825, 829, 830, 832, 835, 836, 840, 842, 843, 844, 845, 846, 847, 848, 849, 852, 854, 857, 859, 860, 861, 862, 863, 867, 871, 872, 873, 874, 875, 885, 890, 896, 911, 914, 916, 944, 952, 954, 963, 972]
Variable Names ==> Fluenc_Arit_CalcFeitos ,Fluenc_Arit_Erros ,Fluenc_Arit_Corretas, Nscreener_Nsimb_Made ,Nscreener_Nsimb_TC ,Numb_Read_81 ,P_Dots_ref32, Verbal_Fluency_An_Corrects ,Stroop_Vic_Color ,Banuca2_AS_1 ,Banuca2_AS_2, Banuca2_AS_3 ,Banuca2_AS_5 ,Banuca2_AS_6 ,Banuca2_AS_7, Banuca2_AS_7_resp, Banuca2_AS_8_resp ,Banuca3_C_3 ,Banuca3_C_4 ,Banuca3_C_5 ,Banuca4_SS_1, Banuca4_SS_2 ,Banuca4_SS_3 ,Banuca4_SS_4 ,Banuca4_SS_5 Banuca4_SS_1_resp, Banuca4_SS_2_resp ,Banuca4_SS_3_resp ,Banuca4_SS_4_resp ,Banuca5_LN_2, Banuca5_LN_3 ,Banuca5_LN_4 ,Banuca5_LN_5 ,Banuca5_LN_6 ,Banuca5_LN_7, Banuca5_LN_8 ,Banuca5_LN_7_resp ,Banuca5_LN_8_resp ,Banuca6_CN_1, Banuca6_CN_5 ,Banuca6_CN_6 ,Banuca6_CN_8 ,Banuca6_CN_1_resp, Banuca6_CN_2_resp ,Banuca6_CN_6_resp ,Banuca6_CN_8_resp, Banuca6_CN_9_resp ,Banuca6_CN_10_resp ,Banuca7_RN_1 ,Banuca7_RN_2, Banuca7_RN_3 ,Banuca7_RN_4 ,Banuca7_RN_5 ,Banuca7_RN_8,Banuca7_RN_2_resp, Banuca7_RN_5_resp ,Banuca7_RN_7_resp ,Banuca7_RN_8_resp ,Banuca8_CM_1, Banuca8_CM_2 ,Banuca8_CM_3 ,Banuca8_CM_7 ,Banuca8_CM_1_resp, Banuca8_CM_2_resp ,Banuca8_CM_3_resp ,Banuca8_CM_4_resp Banuca8_CM_5_resp ,Banuca9_RA_5 ,Banuca9_RA_10 ,Banuca9_RA_1_resp, Fgnosia_RH_visivel ,
Fgnosia_LH_visivel ,Fgnosia_LH_dois_dedos ,Num_Line_Paper_Ajust_Linear, Span_PP_7 ,mult_comp_med1 ,mult_comp_dp1 ,mult_comp_acc1 ,

23==>[38, 39, 450, 456, 457, 460, 461, 469, 475, 476]
Variable Names ==> Fluenc_Arit_CalcPulados ,Fluenc_Arit_Tempo ,CB_car ,CB_dvd ,CB_mcw ,CB_water ,CB_street ,CB_car_score ,CB_dvd_score ,CB_mw_score ,

33==>[42, 43, 53, 54, 76, 83, 526, 753, 868, 886, 910, 960]
Variable Names ==> Nscreener_Simb_Made ,Nscreener_Simb_TC ,Five_Dig_Inhibit_RT ,Five_Dig_Flexib_RT ,Add_S_Time ,P_Digits_1digitcomparison ,MAQ_HW_02 ,Rey_rec2_7 ,Banuca8_CM_8 ,Banuca9_RA_6 ,Banuca9_RA_15_resp ,mult_comp_med7 ,

35==>[46, 492, 511, 571, 734, 735, 736, 737, 743, 755, 758, 858, 876]
Variable Names ==> Reading_Fluency_Time ,OV_CB_np ,MAQ_EC_03 ,Rey_copy_7 ,Rey_rec1_6 ,Rey_rec1_7 ,Rey_rec1_8 ,Rey_rec1_9 ,Rey_rec1_15 ,Rey_rec2_9 ,Rey_rec2_12 ,Banuca7_RN_6_resp ,Banuca8_CM_6_resp ,

52==>[47, 48, 62, 540, 542, 545, 547, 554, 618, 619, 621, 633, 651, 652, 654, 658, 663, 664, 669, 670, 671, 674, 675, 677, 678, 680, 682, 683, 684, 685, 686, 687, 688, 689, 690, 691, 692, 831, 918, 919]
Variable Names ==> Reading_Fluency_LP ,Reading_Fluency_Errors ,Leit_Pseudo_40 ,Pho_Elis_09 ,Pho_Elis_11 ,Pho_Elis_14 ,Pho_Elis_16 ,Pho_Elis_23 ,Digits_arcsine_4 ,Digits_arcsine_6 ,
Digits_arcsine_8 ,TDE_Read_11 ,TDE_Read_29 ,TDE_Read_30 ,
TDE_Read_32 ,TDE_Read_36 ,TDE_Read_41 ,TDE_Read_42 ,TDE_Read_47 ,
TDE_Read_48 ,TDE_Read_49 ,TDE_Read_52 ,TDE_Read_53 ,
TDE_Read_55 ,TDE_Read_56 ,
TDE_Read_58 ,TDE_Read_60 ,TDE_Read_61 ,TDE_Read_62 ,TDE_Read_63 ,TDE_Read_64 ,TDE_Read_65 ,TDE_Read_66 ,TDE_Read_67 ,TDE_Read_68 ,TDE_Read_69 ,TDE_Read_70 ,Banuca6_CN_7 ,
Fgnosias_RLH_escondido ,Fgnosias_RLH_dois_dedos ,

40==>[56, 57, 234, 235, 236, 237, 238, 239, 240, 241, 242, 243, 244, 245, 246, 247, 249, 250, 251, 253, 254, 262, 263, 264, 265, 267, 270, 271, 272, 273, 274, 275, 276, 277, 278, 279, 281, 282, 284, 287, 300, 305, 388, 774]
Variable Names ==> Multidigits_T_Adicao ,Multidigits_T_Sub ,NumRead_2 ,NumRead_3 ,NumRead_4 ,NumRead_5 ,NumRead_6 ,NumRead_7 ,NumRead_8 ,NumRead_9 ,NumRead_10 ,NumRead_11 ,NumRead_12 ,NumRead_13 ,NumRead_14 ,NumRead_15 ,NumRead_17 ,NumRead_18 ,NumRead_19 ,NumRead_21 ,NumRead_22 ,NumRead_R_2 ,NumRead_R_3 ,NumRead_R_4 ,NumRead_R_5 ,NumRead_R_7 ,NumRead_R_10 ,NumRead_R_11 ,NumRead_R_12 ,NumRead_R_13 ,NumRead_R_14 ,NumRead_R_15 ,NumRead_R_17 ,NumRead_R_18 ,NumRead_R_19 ,NumRead_R_20 ,NumRead_R_22 ,NumRead_R_23 ,NumRead_R_25 ,NumRead_R_28 ,Add_S_01_answ ,Add_S_06_answ ,Sub_C_08_answ ,Banuca2_AS_4 ,

2==>[60, 61, 89, 90, 91, 93, 94, 95, 96, 97, 100, 101, 103, 152, 153, 154, 156, 157,

158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169, 170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 199, 201, 202, 226, 301, 506, 757, 766, 767, 770, 878, 1110, 1111, 1112, 1113, 1114, 1115, 1116, 1117, 1118, 1119, 1120, 1121, 1122, 1123, 1124, 1125, 1126, 1127, 1128, 1129, 1130, 1131, 1132, 1133, 1134, 1135, 1136, 1137, 1138, 1139, 1140, 1141, 1142, 1143, 1144, 1145, 1146, 1147, 1148, 1149, 1150, 1151, 1152, 1153, 1154, 1155, 1156, 1157, 1158, 1159, 1160, 1161, 1162, 1163, 1164, 1165, 1166, 1167, 1168, 1169, 1170, 1171, 1172, 1173, 1174, 1175, 1176, 1177, 1178, 1179, 1180, 1181, 1182, 1183, 1184, 1185, 1186, 1187, 1188, 1189, 1190]
Variable Names ==> Warring_operacoes ,Warring_cotidiano ,Verbal_Fluency_An_Errors, Five_Points_orig ,Five_Points_repet ,RAVLT_LA_1 ,RAVLT_LA_2 ,RAVLT_LA_3, RAVLT_LA_4 ,RAVLT_LA_5 ,RAVLT_LA_7 ,RAVLT_Reconhec ,Stroop_Vic_ColorW, Transc81_01_answ ,Transc81_02_answ ,Transc81_03_answ ,Transc81_05_answ, Transc81_06_answ ,Transc81_07_answ ,Transc81_08_answ ,Transc81_09_answ, Transc81_10_answ ,Transc81_11_answ ,Transc81_12_answ ,Transc81_13_answ, Transc81_14_answ ,Transc81_15_answ ,Transc81_16_answ ,Transc81_17_answ, Transc81_18_answ ,Transc81_19_answ ,Transc81_20_answ ,Transc81_21_answ, Transc81_22_answ ,Transc81_23_answ ,Transc81_24_answ ,Transc81_25_answ, Transc81_26_answ ,Transc81_27_answ ,Transc81_28_answ ,Transc81_48_answ, Transc81_50_answ ,Transc81_51_answ ,Transc81_75_answ ,Add_S_02_answ, MAQ_GM_02 ,Rey_rec2_11 ,Banuca1_CP_2 ,Banuca1_CP_3 ,Banuca1_CP_6, Banuca8_CM_8_resp ,Transc81_01 ,Transc81_02 ,Transc81_03 ,Transc81_04, Transc81_05 ,Transc81_06 ,Transc81_07 ,Transc81_08 ,Transc81_09 ,Transc81_10, Transc81_11 ,Transc81_12 ,Transc81_13 ,Transc81_14 ,Transc81_15 ,Transc81_16, Transc81_17 ,Transc81_18 ,Transc81_19 ,Transc81_20 ,Transc81_21 ,Transc81_22, ,Transc81_23 ,Transc81_24 ,Transc81_25 ,Transc81_26 ,Transc81_27 ,Transc81_28, ,Transc81_29 ,Transc81_30 ,Transc81_31 ,Transc81_32 ,Transc81_33 ,Transc81_34 ,Transc81_35 ,Transc81_36 ,Transc81_37 ,Transc81_38 ,Transc81_39 ,Transc81_40 ,Transc81_41 ,Transc81_42 ,Transc81_43 ,Transc81_44 ,Transc81_45 ,Transc81_46 ,Transc81_47 ,Transc81_48 ,Transc81_49 ,Transc81_50 ,Transc81_51 ,Transc81_52 ,Transc81_53 ,Transc81_54 ,Transc81_55 ,Transc81_56 ,Transc81_57 ,Transc81_58 ,Transc81_59 ,Transc81_60 ,Transc81_61 ,Transc81_62 ,Transc81_63 ,Transc81_64 ,Transc81_65 ,Transc81_66 ,Transc81_67 ,Transc81_68 ,Transc81_69 ,Transc81_70 ,Transc81_71 ,Transc81_72 ,Transc81_73 ,Transc81_74 ,Transc81_75 ,Transc81_76 ,Transc81_77 ,Transc81_78 ,Transc81_79 ,Transc81_80 ,Transc81_81 ,

4==>[63, 112, 113, 114, 116, 117, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142, 143, 144, 145, 146, 147, 148, 149, 150, 151, 525, 895]
Variable Names ==> Repet_Pseudo_15 ,Transc_R_1 ,Transc_R_2 ,Transc_R_3 ,Transc_R_5 ,Transc_R_6 ,Transc_R_7 ,Transc_R_8 ,Transc_R_9 ,Transc_R_10

,Transc_R_11 ,Transc_R_12 ,Transc_R_13 ,Transc_R_14 ,Transc_R_15 ,Transc_R_16 ,Transc_R_17 ,Transc_R_18 ,Transc_R_19 ,Transc_R_20 ,Transc_R_21 ,Transc_R_22 ,Transc_R_23 ,Transc_R_24 ,Transc_R_25 ,Transc_R_26 ,Transc_R_27 ,Transc_R_28 ,Transc_R_29 ,Transc_R_30 ,Transc_R_31 ,Transc_R_32 ,Transc_R_33 ,Transc_R_34 ,Transc_R_35 ,Transc_R_36 ,Transc_R_37 ,Transc_R_38 ,Transc_R_39 ,Transc_R_40 ,MAQ_HW_01 ,Banuca9_RA_15 ,

51==>[65, 365, 389, 405, 406, 407, 408, 409, 419, 549, 667, 798, 800, 891, 894, 956, 957, 958, 959, 961, 962, 964, 965, 967, 968, 970, 971, 973, 974, 975, 976, 977, 978, 979, 980]
Variable Names ==> Repet_Pseudo_40 ,Sub_S_12_answ ,Sub_C_09_answ ,Mul_S_10_answ ,Mul_S_11_answ ,Mul_S_12_answ ,Mul_S_13_answ ,Mul_S_14_answ ,Mul_C_09_answ ,Pho_Elis_18 ,TDE_Read_45 ,Banuca4_SS_6 ,Banuca4_SS_8
, Banuca9_RA_11 ,Banuca9_RA_14 ,mult_comp_med3 ,mult_comp_med4 ,mult_comp_med5 ,mult_comp_med6 ,mult_comp_med8 ,mult_comp_med9 ,mult_comp_dp2 ,mult_comp_dp3 ,mult_comp_dp5 ,mult_comp_dp6 ,mult_comp_dp8 ,mult_comp_dp9 ,mult_comp_acc2 ,mult_comp_acc3 ,mult_comp_acc4 ,mult_comp_acc5 ,mult_comp_acc6 ,mult_comp_acc7 ,mult_comp_acc8 ,mult_comp_acc9 ,

6==>[66, 67, 68, 69, 856, 1328]
Variable Names ==> RAN_1 ,RAN_2 ,RAN_3 ,RAN_4 ,Banuca7_RN_4_resp ,CBCL_77
,

42==>[70, 288, 289, 290, 291, 292, 293, 302, 306, 308, 312, 313, 314, 315, 316, 327, 328, 330, 331, 332, 342, 343, 347, 348, 349, 360, 369, 431, 432, 435, 443, 444, 447, 538, 807, 866, 879, 880]
Variable Names ==> RAN_1_erros ,Add_S_01 ,Add_S_02 ,Add_S_03 ,Add_S_04 , Add_S_05 ,Add_S_06 ,Add_S_03_answ ,Add_S_07_answ ,Add_S_09_answ ,Add_C_01 ,Add_C_02 ,Add_C_03 ,Add_C_04 ,Add_C_05 ,Add_C_01_answ ,Add_C_02_answ ,Add_C_04_answ ,Add_C_05_answ ,Add_C_06_answ ,Sub_S_01 ,Sub_S_02 ,Sub_S_06 ,Sub_S_07 ,Sub_S_08 ,Sub_S_07_answ ,Sub_C_04 ,Prob_08 ,Prob_09 ,Prob_12 ,Prob_R_8 ,Prob_R_9 ,Prob_R_12 ,Pho_Elis_07 ,Banuca4_SS_7_resp ,Banuca8_CM_6 ,Banuca8_CM_9_resp ,Banuca8_CM_10_resp ,

15==>[71, 72, 73, 115, 261, 500, 583, 593, 599, 693, 696, 697, 698, 699, 705, 706, 707, 708, 709, 710, 717, 718, 722, 723, 725, 769, 787, 809, 817, 853, 917, 946, 947, 948, 949, 950]
Variable Names ==> RAN_2_erros ,RAN_3_erros ,RAN_4_erros ,Transc_R_4 ,Num-Read_R_1 ,OV_CB_ref_score ,Est_median_1 ,Est_median_56 ,Est_RT_mean_5 ,Orient_1 ,Orient_4 ,Orient_5 ,Orient_6 ,Orient_7 ,Fgnosia_RH_1 ,Fgnosia_RH_2 ,Fgnosia_RH_3 ,Fgnosia_RH_4 ,Fgnosia_RH_5 ,Fgnosia_RH_6 ,Fgnosia_LH_1 ,Fgnosia_LH_2 ,Fgnosia_LH_6 ,Fgnosia_LH_7 ,Fgnosia_LH_9 ,Banuca1_CP_5 ,Banuca3_C_1 ,Banuca5_LN_1 ,Banuca5_LN_1_resp ,Banuca7_RN_1_resp ,Fgnosias_RLH_visivel

,Span_PP_1 ,Span_PP_2 ,Span_PP_3 ,Span_PP_4 ,Span_PP_5 ,

7==>[74, 75, 520, 1246, 1249, 1250, 1253, 1256, 1259, 1261, 1262, 1268, 1273, 1274, 1275, 1276, 1283, 1284, 1286, 1290, 1291, 1293, 1294, 1295, 1296, 1297, 1298, 1299, 1300, 1301, 1302, 1303, 1304, 1305, 1306, 1307, 1309, 1310, 1311, 1314, 1316, 1317, 1318, 1320, 1321, 1322, 1323, 1324, 1326, 1327, 1330, 1331, 1332, 1333, 1334, 1335, 1336, 1342, 1343, 1347, 1348, 1349, 1350, 1351, 1352, 1353, 1354, 1356, 1357, 1358, 1359, 1361, 1362, 1363, 1364]
Variable Names ==> CBCL_SomaticComplaints_SN ,CBCL_SomaticProblems_SN ,MAQ_WC_04 ,CBCL_2 ,CBCL_5 ,CBCL_6 ,CBCL_9 ,CBCL_12 ,CBCL_15 ,CBCL_17 ,CBCL_18 ,CBCL_24 ,CBCL_29 ,CBCL_30 ,CBCL_31 ,CBCL_32 ,CBCL_39 ,CBCL_40 ,CBCL_42 ,CBCL_46 ,CBCL_47 ,CBCL_49 ,CBCL_50 ,CBCL_51 ,CBCL_52 ,CBCL_53 ,CBCL_54 ,CBCL_55 ,CBCL_56_a ,CBCL_56_b ,CBCL_56_c ,CBCL_56_d ,CBCL_56_e ,CBCL_56_f ,CBCL_56_g ,CBCL_56_h ,CBCL_58 ,CBCL_59 ,CBCL_60 ,CBCL_63 ,CBCL_65 ,CBCL_66 ,CBCL_67 ,CBCL_69 ,CBCL_70 ,CBCL_71 ,CBCL_72 ,CBCL_73 ,CBCL_75 ,CBCL_76 ,CBCL_79 ,CBCL_80 ,CBCL_81 ,CBCL_82 ,CBCL_83 ,CBCL_84 ,CBCL_85 ,CBCL_91 ,CBCL_92 ,CBCL_96 ,CBCL_97 ,CBCL_98 ,CBCL_99 ,CBCL_100 ,CBCL_101 ,CBCL_102 ,CBCL_103 ,CBCL_105 ,CBCL_106 ,CBCL_107 ,CBCL_108 ,CBCL_110 ,CBCL_111 ,CBCL_112 ,CBCL_113 ,

29==>[77, 78, 79, 80, 233, 379, 380, 955]
Variable Names ==> Add_C_Time ,Sub_S_Time ,Sub_C_Time ,Mul_S_Time ,Num-Read_1 ,Sub_C_14 ,Sub_C_15 ,mult_comp_med2 ,

58==>[81, 344, 345, 346, 354, 355, 356, 358, 359, 361, 381, 382, 383, 384, 385, 516, 529, 560, 623, 738, 920, 926, 931, 942, 966, 981]
Variable Names ==> Mul_C_Time ,Sub_S_03 ,Sub_S_04 ,Sub_S_05 ,Sub_S_01_answ ,Sub_S_02_answ ,Sub_S_03_answ ,Sub_S_05_answ ,Sub_S_06_answ ,Sub_S_08_answ ,Sub_C_01_answ ,Sub_C_02_answ ,Sub_C_03_answ ,Sub_C_04_answ ,Sub_C_05_answ ,MAQ_DC_04 ,LPI_Reg_Porcentagem ,Five_Dig_Read_E ,TDE_Read_1 ,Rey_rec1_10 ,Num_Line_Paper_4 ,Num_Line_Paper_8 ,Num_Line_Paper_3 ,Num_Line_Paper_6 ,mult_comp_dp4 ,Ideb ,

17==>[84, 85, 86, 87, 519, 1228, 1229, 1230, 1231, 1232, 1233, 1234, 1235, 1236]
Variable Names ==> SNAP_Mean_ADHD_inattention ,SNAP_Mean_ADHD_hyperactivity ,SNAP_Mean_ADHD_combined ,SNAP_Mean_ODD ,MAQ_WC_03 ,SNAP_10 ,SNAP_11 ,SNAP_12 ,SNAP_13 ,SNAP_14 ,SNAP_15 ,SNAP_16 ,SNAP_17 ,SNAP_18 ,

37==>[98, 99, 311, 333, 334, 505, 509, 510, 517, 528, 566, 702, 730, 788, 897, 904]
Variable Names ==> RAVLT_LB_1 ,RAVLT_LA_6 ,Add_S_12_answ ,Add_C_07_answ ,Add_C_08_answ ,MAQ_GM_01 ,MAQ_EC_01 ,MAQ_EC_02 ,MAQ_WC_01 ,MAQ_HW_04 ,Rey_copy_2 ,Orient_10 ,Rey_rec1_2 ,Banuca3_C_2 ,Banuca9_RA_2_resp , Banuca9_RA_9_resp ,

1==>[104, 105, 180, 181, 182, 183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194, 195, 196, 197, 198, 200, 203, 204, 205, 206, 207, 208, 209, 210, 211, 212, 213, 214, 215, 216, 217, 218, 219, 220, 221, 222, 223, 224, 225, 227, 228, 229, 230, 231, 232, 768]
Variable Names ==> Stroop_Vic_Incongr ,Stroop_Vic_Interf ,Transc81_29_answ , Transc81_30_answ ,Transc81_31_answ ,Transc81_32_answ ,Transc81_33_answ , Transc81_34_answ ,Transc81_35_answ ,Transc81_36_answ ,Transc81_37_answ ,Transc81_38_answ ,Transc81_39_answ ,Transc81_40_answ ,Transc81_41_answ ,Transc81_42_answ ,Transc81_43_answ ,Transc81_44_answ ,Transc81_45_answ ,Transc81_46_answ ,Transc81_47_answ ,Transc81_49_answ ,Transc81_52_answ ,Transc81_53_answ ,Transc81_54_answ ,Transc81_55_answ ,Transc81_56_answ ,Transc81_57_answ ,Transc81_58_answ ,Transc81_59_answ ,Transc81_60_answ ,Transc81_61_answ ,Transc81_62_answ ,Transc81_63_answ ,Transc81_64_answ ,Transc81_65_answ ,Transc81_66_answ ,Transc81_67_answ ,Transc81_68_answ ,Transc81_69_answ ,Transc81_70_answ ,Transc81_71_answ ,Transc81_72_answ ,Transc81_73_answ ,Transc81_74_answ ,Transc81_76_answ ,Transc81_77_answ ,Transc81_78_answ ,Transc81_79_answ ,Transc81_80_answ ,Transc81_81_answ ,Banuca1_CP_4 ,

60==>[252, 255, 256, 257, 258, 259, 260, 532]
Variable Names ==> NumRead_20 ,NumRead_23 ,NumRead_24 ,NumRead_25 ,NumRead_26 ,NumRead_27 ,NumRead_28 ,Pho_Elis_01 ,

56==>[269, 283, 285, 286, 624, 631, 632, 740, 756]
Variable Names ==> NumRead_R_9 ,NumRead_R_24 ,NumRead_R_26 ,NumRead_R_27 ,TDE_Read_2
,TDE_Read_9 ,TDE_Read_10 ,Rey_rec1_12 ,Rey_rec2_10 ,

59==>[294, 295, 296, 297, 298, 299, 307, 309, 310, 317, 320, 321, 335, 350, 351, 352, 362, 363, 364, 372, 387, 397, 427, 851]
Variable Names ==> Add_S_07 ,Add_S_08 ,Add_S_09 ,Add_S_10 ,Add_S_11 ,Add_S_12 ,Add_S_08_answ ,Add_S_10_answ ,Add_S_11_answ ,Add_C_06 ,Add_C_09 ,Add_C_10 ,Add_C_09_answ ,Sub_S_09 ,Sub_S_10 ,Sub_S_11 ,Sub_S_09_answ ,Sub_S_10_answ ,Sub_S_11_answ ,Sub_C_07 ,Sub_C_07_answ ,Mul_S_02_answ ,Prob_04 ,Banuca7_RN_7 ,

63==>[318, 322, 323, 324, 325, 326, 353, 366, 367, 368, 370, 371, 373, 374, 375, 376, 377]
Variable Names ==> Add_C_07 ,Add_C_11 ,Add_C_12 ,Add_C_13 ,Add_C_14 ,Add_C_15 ,Sub_S_12 ,Sub_C_01 ,Sub_C_02 ,Sub_C_03 ,Sub_C_05 ,Sub_C_06 ,Sub_C_08 ,Sub_C_09 ,Sub_C_10 ,Sub_C_11 ,Sub_C_12 ,

48==>[336, 337, 338, 339, 340, 341, 390, 391, 392, 393, 394, 395]
Variable Names ==> Add_C_10_answ ,Add_C_11_answ ,Add_C_12_answ ,Add_C_13_answ

,Add_C_14_answ ,Add_C_15_answ ,Sub_C_10_answ ,Sub_C_11_answ ,Sub_C_12_answ ,Sub_C_13_answ ,Sub_C_14_answ ,Sub_C_15_answ ,

50==>[378, 464, 465, 676, 779, 780, 781, 783, 784, 806, 808, 818, 819, 820, 821, 827, 837, 855, 881, 884, 899, 900, 901, 906, 909]
Variable Names ==> Sub_C_13 ,CB_People_House ,CB_People_bedroom ,TDE_Read_54 ,Banuca2_AS_1_resp ,Banuca2_AS_2_resp ,Banuca2_AS_3_resp ,Banuca2_AS_5_resp ,Banuca2_AS_6_resp ,Banuca4_SS_6_resp ,Banuca4_SS_8_resp ,Banuca5_LN_2_resp ,Banuca5_LN_3_resp ,Banuca5_LN_4_resp ,Banuca5_LN_5_resp ,Banuca6_CN_3 ,Banuca6_CN_3_resp ,Banuca7_RN_3_resp ,Banuca9_RA_1 ,Banuca9_RA_4 ,Banuca9_RA_4_resp ,Banuca9_RA_5_resp ,Banuca9_RA_6_resp ,Banuca9_RA_11_resp ,Banuca9_RA_14_resp ,

39==>[399, 400, 1191, 1192, 1193, 1194, 1195, 1196, 1197, 1198, 1199, 1200, 1201, 1202, 1203, 1204, 1205, 1206, 1207, 1208, 1209, 1210, 1211, 1212, 1213, 1214, 1215, 1216, 1217, 1218]
Variable Names ==> Mul_S_04_answ ,Mul_S_05_answ ,Mul_S_01 ,Mul_S_02 ,Mul_S_03 ,Mul_S_04 ,Mul_S_05 ,Mul_S_06 ,Mul_S_07 ,Mul_S_08 ,Mul_S_09 ,Mul_S_10 ,Mul_S_11 ,Mul_S_12 ,Mul_S_13 ,Mul_S_14 ,Mul_S_15 ,Mul_C_01 ,Mul_C_02 ,Mul_C_03 ,Mul_C_04 ,Mul_C_05 ,Mul_C_06 ,Mul_C_07 ,Mul_C_08 ,Mul_C_09 ,Mul_C_10 ,Mul_C_11 ,Mul_C_12 ,Mul_C_13 ,

55==>[404, 530, 531, 558, 625, 626, 627, 628, 629, 630, 635, 636, 637, 638, 639, 640, 642, 643, 644, 645, 646, 647, 648, 649, 650, 653, 655, 657, 659, 660, 661, 665, 666, 668, 672, 673, 679, 681, 826]
Variable Names ==>
Mul_S_09_answ ,LPI_Irreg_Porcentagem ,LPI_Pseud_Porcentagem ,Pho_Elis_27
TDE_Read_3 ,TDE_Read_4 ,TDE_Read_5 ,TDE_Read_6 ,TDE_Read_7 ,TDE_Read_8 ,TDE_Read_13 ,TDE_Read_14 ,TDE_Read_15 ,TDE_Read_16 ,TDE_Read_17 ,TDE_Read_18 ,TDE_Read_20 ,TDE_Read_21 ,TDE_Read_22 ,TDE_Read_23 ,TDE_Read_24 ,TDE_Read_25 ,TDE_Read_26 ,TDE_Read_27 ,TDE_Read_28 ,TDE_Read_31 ,TDE_Read_33 ,TDE_Read_35 ,TDE_Read_37 ,TDE_Read_38 ,TDE_Read_39 ,TDE_Read_43 ,TDE_Read_44 ,TDE_Read_46 ,TDE_Read_50 ,TDE_Read_51 ,TDE_Read_57 ,TDE_Read_59 ,Banuca6_CN_2

64==>[411, 412, 413, 414, 415, 416, 417, 418, 420, 421, 422, 423, 870, 903]
Variable Names ==> Mul_C_01_answ ,Mul_C_02_answ ,Mul_C_03_answ ,Mul_C_04_answ ,Mul_C_05_answ ,Mul_C_06_answ ,Mul_C_07_answ ,Mul_C_08_answ ,Mul_C_10_answ ,Mul_C_11_answ ,Mul_C_12_answ ,Mul_C_13_answ ,Banuca8_CM_10 ,Banuca9_RA_8_resp

61==>[424, 425, 426, 428, 429, 430, 433, 434, 436, 438, 440, 441, 442, 445, 446]
Variable Names ==> Prob_01 ,Prob_02 ,Prob_03 ,Prob_05 ,Prob_06 ,Prob_07 ,Prob_10

,Prob_11 ,Prob_R_1 ,Prob_R_3 ,Prob_R_5 ,Prob_R_6 ,Prob_R_7 ,Prob_R_10 ,Prob_R_11 ,

21==>[448, 449, 454, 458, 459, 467, 468, 473, 477, 478]
Variable Names ==> CB_bath ,CB_maid ,CB_freezer ,CB_moto ,CB_drm ,CB_bath_score ,CB_maid_score ,CB_freezer_score ,CB_moto_score ,CB_drm_score ,

22==>[451, 455, 470, 474, 1001, 1002]
Variable Names ==> CB_computador ,CB_wm ,CB_computer_score ,CB_wm_score ,SES_juntado ,SES_justado_nominal ,

27==>[462, 463, 466, 481, 527, 750, 752, 754, 1000]
Variable Names ==>
CB_Father_educ ,CB_Mother_educ ,CB_income ,CB_housedl_score ,MAQ_HW_03 ,Rey_rec2_4 ,Rey_rec2_6 ,Rey_rec2_8 ,Consistencia_Lat_HYF ,

20==>[482, 485, 487, 488, 489, 493, 496, 498, 499]
Variable Names ==>
OV_CB_tv ,OV_CB_car ,OV_CB_wm ,OV_CB_dvd ,OV_CB_ref ,OV_CB_tv_score ,OV_CB_car_score ,OV_CB_wm_score ,OV_CB_dvd_score ,

19==>[483, 484, 486, 490, 494, 495, 497, 501, 634]
Variable Names ==> OV_CB_radio ,OV_CB_bath ,OV_CB_hm ,OV_CB_freezer ,OV_CB_radio_score ,OV_CB_bath_score ,OV_CB_hm_score ,OV_CB_freezer_score ,TDE_Read_12 ,

26==>[491, 502, 503, 504, 662, 865]
Variable Names ==> OV_CB_iy ,OV_CB_iy_score ,OV_Mother_ed_level ,OV_Father_ed_level ,TDE_Read_40 ,Banuca8_CM_5 ,

34==>[507, 729, 739, 746, 888, 969]
Variable Names ==> MAQ_GM_03 ,Rey_rec1_1 ,Rey_rec1_11 ,Rey_rec1_18 ,Banuca9_RA_8 ,mult_comp_dp7 ,

18==>[512, 882, 925, 1219, 1220, 1221, 1222, 1223, 1224, 1225, 1226, 1227]
Variable Names ==> MAQ_EC_04 ,Banuca9_RA_2 ,Num_Line_Paper_64 ,SNAP_1 ,SNAP_2 ,SNAP_3 ,SNAP_4 ,SNAP_5 ,SNAP_6 ,SNAP_7 ,SNAP_8 ,SNAP_9 ,

32==>[513, 514, 515, 518, 521, 522, 524]
Variable Names ==> MAQ_DC_01 ,MAQ_DC_02 ,MAQ_DC_03 ,MAQ_WC_02 ,MAQ_MC_01 ,MAQ_MC_02 ,MAQ_MC_04 ,

62==>[534, 535, 536, 537, 539, 541, 544, 546, 548, 550, 551, 552, 553, 555, 556, 557, 559, 564, 761, 893]
Variable Names ==> Pho_Elis_03 ,Pho_Elis_04 ,Pho_Elis_05 ,Pho_Elis_06 ,Pho_Elis_08 ,Pho_Elis_10 ,Pho_Elis_13 ,Pho_Elis_15 ,Pho_Elis_17 ,Pho_Elis_19 ,Pho_Elis_20

,Pho_Elis_21 ,Pho_Elis_22 ,Pho_Elis_24 ,Pho_Elis_25 ,Pho_Elis_26 ,Pho_Elis_28 ,Pho_Elis_Percentage ,Rey_rec2_15 ,Banuca9_RA_13 ,

53==>[565, 567, 568, 569, 570, 572, 573, 574, 575, 576, 579, 580, 581, 732, 733, 744, 745, 747, 762, 763]
Variable Names ==> Rey_copy_1 ,Rey_copy_3 ,Rey_copy_4 ,Rey_copy_5 ,Rey_copy_6 ,Rey_copy_8 ,Rey_copy_9 ,Rey_copy_10 ,Rey_copy_11 ,Rey_copy_12 ,Rey_copy_15 ,Rey_copy_16 ,Rey_copy_17 ,Rey_rec1_4 ,Rey_rec1_5 ,Rey_rec1_16 ,Rey_rec1_17 ,Rey_rec2_1 ,Rey_rec2_16 ,Rey_rec2_17 ,

11==>[584, 585, 586, 587, 588, 589, 590, 591, 592, 594, 595, 596, 597, 598, 600, 601, 602, 603, 604, 605, 606]
Variable Names ==>
Est_median_2 ,Est_median_3 ,Est_median_4 ,Est_median_5 ,Est_median_10 ,Est_median_16 ,Est_median_24 ,Est_median_32 ,Est_median_48 ,Est_median_64 ,Est_RT_mean_1 ,Est_RT_mean_2 ,Est_RT_mean_3 ,Est_RT_mean_4 ,Est_RT_mean_10 ,Est_RT_mean_16 ,Est_RT_mean_24 ,Est_RT_mean_32 ,Est_RT_mean_48 ,Est_RT_mean_56 ,Est_RT_mean_64 ,

43==>[656, 1366, 1367, 1368, 1369, 1370, 1371, 1372, 1373, 1374, 1375, 1376, 1377, 1378, 1379, 1380, 1381, 1382, 1383, 1384, 1385, 1386, 1387, 1388, 1389, 1390, 1391, 1392, 1393, 1394, 1395, 1396, 1397, 1398, 1399]
Variable Names ==>
TDE_Read_34 ,TDE_Spell_1 ,TDE_Spell_2 ,TDE_Spell_3 ,TDE_Spell_4 ,TDE_Spell_5 ,TDE_Spell_6 ,TDE_Spell_7 ,TDE_Spell_8 ,TDE_Spell_9 ,TDE_Spell_10 ,TDE_Spell_11 ,TDE_Spell_12 ,TDE_Spell_13 ,TDE_Spell_14 ,TDE_Spell_15 ,TDE_Spell_16 ,TDE_Spell_17 ,TDE_Spell_18 ,TDE_Spell_19 ,TDE_Spell_20 ,TDE_Spell_21 ,TDE_Spell_22 ,TDE_Spell_23 ,TDE_Spell_24 ,TDE_Spell_25 ,TDE_Spell_26 ,TDE_Spell_27 ,TDE_Spell_28 ,TDE_Spell_29 ,TDE_Spell_30 ,TDE_Spell_31 ,TDE_Spell_32 ,TDE_Spell_33 ,TDE_Spell_34

5==>[764, 1245, 1247, 1248, 1251, 1252, 1254, 1255, 1257, 1258, 1260, 1263, 1264, 1265, 1266, 1267, 1269, 1270, 1271, 1272, 1277, 1278, 1279, 1280, 1281, 1282, 1285, 1287, 1288, 1289, 1292, 1308, 1312, 1313, 1315, 1319, 1325, 1329, 1337, 1338, 1339, 1340, 1341, 1344, 1345, 1346, 1355, 1360]
Variable Names ==> Rey_rec2_18 ,CBCL_1 ,CBCL_3 ,CBCL_4 ,CBCL_7 ,CBCL_8 ,CBCL_10 ,CBCL_11 ,CBCL_13 ,CBCL_14 ,CBCL_16 ,CBCL_19 ,CBCL_20 ,CBCL_21 ,CBCL_22 ,CBCL_23 ,CBCL_25 ,CBCL_26 ,CBCL_27 ,CBCL_28 ,CBCL_33 ,CBCL_34 ,CBCL_35 ,CBCL_36 ,CBCL_37 ,CBCL_38 ,CBCL_41 ,CBCL_43 ,CBCL_44 ,CBCL_45 ,CBCL_48 ,CBCL_57 ,CBCL_61 ,CBCL_62 ,CBCL_64 ,CBCL_68 ,CBCL_74 ,CBCL_78 ,CBCL_86 ,CBCL_87 ,CBCL_88 ,CBCL_89 ,CBCL_90 ,CBCL_93 ,CBCL_94 ,CBCL_95

,CBCL_104 ,CBCL_109 ,

28==>[765, 805, 822, 839, 869, 877, 902, 905]
Variable Names ==> Banuca1_CP_1 ,Banuca4_SS_5_resp ,Banuca5_LN_6_resp ,Banuca6_CN_5_resp ,Banuca8_CM_9 ,Banuca8_CM_7_resp ,Banuca9_RA_7_resp ,Banuca9_RA_10_resp ,

31==>[778, 921, 923, 924, 927, 928, 935, 936, 940, 943]
Variable Names ==> Banuca2_AS_8 ,Num_Line_Paper_79 ,Num_Line_Paper_84 ,Num_Line_Paper_61 ,Num_Line_Paper_81 ,Num_Line_Paper_90 ,Num_Line_Paper_96 ,Num_Line_Paper_52 ,Num_Line_Paper_57 ,Num_Line_Paper_72 ,

9==>[892, 907, 988, 989, 990, 991, 992, 1545, 1559, 1560]
Variable Names ==>
Banuca9_RA_12 ,Banuca9_RA_12_resp ,NM_Fgnosia_RH_1 ,NM_Fgnosia_RH_2 ,NM_Fgnosia_RH_3 ,NM_Fgnosia_LH_1 ,NM_Fgnosia_LH_2 ,NM_Pantonima1 ,NM_Tanden_frente ,NM_Tanden_tras ,

25==>[922, 929, 930, 932, 933, 934, 937, 938, 939, 941]
Variable Names ==> Num_Line_Paper_23 ,Num_Line_Paper_12 ,Num_Line_Paper_25 ,Num_Line_Paper_39 ,Num_Line_Paper_17 ,Num_Line_Paper_48 ,Num_Line_Paper_21 ,Num_Line_Paper_43 ,Num_Line_Paper_29 ,Num_Line_Paper_33 ,

30==>[982, 983, 984, 985, 986, 987, 994]
Variable Names ==> FT_D_1 ,FT_D_2 ,FT_RH_mean_final ,FT_E_1 ,FT_E_2 ,FT_LH_mean_final ,NM_Estereotipias ,

10==>[993, 995, 996, 997, 998, 999, 1006, 1069, 1534, 1535, 1536, 1537, 1538, 1539, 1540, 1541, 1542, 1543, 1544, 1546, 1547, 1548, 1549, 1550, 1551, 1552, 1553, 1554, 1556, 1557, 1561, 1562, 1563, 1564, 1565, 1566, 1567, 1568, 1569, 1570, 1571]

Variable Names ==>
NM_Fgnosia_LH_3 ,NM_index_nose_eyes_open ,NM_index_nose_eyes_close ,NM_Marcha_unip_D ,NM_Marcha_unip_E ,Consistencia_Lat_H ,preferencia_manual ,hand_preferencia ,NM_Lat_H_1 ,NM_Lat_H_2 ,NM_Lat_H_3 ,NM_Lat_H_result ,NM_Lat_Y_1 ,NM_Lat_Y_2 ,NM_Lat_Y_3 ,NM_Lat_Y_result ,NM_Lat_F_result ,NM_Moeda_D ,NM_Moeda_E ,NM_Pantonima2 ,NM_Pantonima3 ,NM_Pantonima4 ,NM_Pantonima5 ,NM_Pantonima6 ,SequenciaMotora ,InstrucesConflitantes ,GonoGo ,index_index ,Disdiadococinesia ,Oseretski ,NM_Romberg ,NM_Reacao_eq_frente ,NM_Reacao_eq_tras ,NM_Reacao_eq_lat ,NM_Corrida ,NM_Marcha_ponta_pe ,NM_Marcha_calcanhar ,NM_Apoio_unipodal ,NM_Salto_palmas ,NM_Polichinelo ,NM_Coordenacao ,

41==>[1007, 1008, 1009, 1010, 1011, 1012, 1013, 1014, 1015, 1016, 1023, 1024,

1025, 1026, 1027, 1028, 1029, 1030, 1039, 1040, 1041, 1042, 1043, 1044, 1045, 1046, 1047, 1048, 1055, 1056, 1057, 1058, 1059, 1060]
Variable Names ==> Corsi_F_1_1 ,Corsi_F_1_2 ,Corsi_F_2_1 ,Corsi_F_2_2 ,Corsi_F_3_1 ,Corsi_F_3_2 ,Corsi_F_4_1 ,Corsi_F_4_2 ,Corsi_F_5_1 ,Corsi_F_5_2 ,Corsi_B_1_1 ,Corsi_B_1_2 ,Corsi_B_2_1 ,Corsi_B_2_2 ,Corsi_B_3_1 ,Corsi_B_3_2 ,Corsi_B_4_1 ,Corsi_B_4_2 ,Dspan_F_1_1 ,Dspan_F_1_2 ,Dspan_F_2_1 ,Dspan_F_2_2 ,Dspan_F_3_1 ,Dspan_F_3_2 ,Dspan_F_4_1 ,Dspan_F_4_2 ,Dspan_F_5_1 ,Dspan_F_5_2 ,Dspan_B_1_1 ,Dspan_B_1_2 ,Dspan_B_2_1 ,Dspan_B_2_2 ,Dspan_B_3_1 ,Dspan_B_3_2 ,

12==>[1017, 1018, 1019, 1020, 1031, 1032, 1033, 1034, 1061, 1062, 1063, 1064]
Variable Names ==> Corsi_F_6_1 ,Corsi_F_6_2 ,Corsi_F_7_1 ,Corsi_F_7_2 ,Corsi_B_5_1 ,Corsi_B_5_2 ,Corsi_B_6_1 ,Corsi_B_6_2 ,Dspan_B_4_1 ,Dspan_B_4_2 ,Dspan_B_5_1 ,Dspan_B_5_2 ,

13==>[1021, 1022, 1053, 1054, 1065, 1066, 1067, 1068]
Variable Names ==>
Corsi_F_8_1 ,Corsi_F_8_2 ,Dspan_F_8_1 ,Dspan_F_8_2 ,Dspan_B_6_1, Dspan_B_6_2 ,Dspan_B_7_1 ,Dspan_B_7_2 ,

14==>[1035, 1036, 1037, 1038, 1049, 1050, 1051, 1052]
Variable Names ==>
Corsi_B_7_1 ,Corsi_B_7_2 ,Corsi_B_8_1 ,Corsi_B_8_2 ,Dspan_F_6_1, Dspan_F_6_2 ,Dspan_F_7_1 ,Dspan_F_7_2 ,

3==>[1070, 1071, 1072, 1073, 1074, 1075, 1076, 1077, 1078, 1079, 1080, 1081, 1082, 1083, 1084, 1085, 1086, 1087, 1088, 1089, 1090, 1091, 1092, 1093, 1094, 1095, 1096, 1097, 1098, 1099, 1100, 1101, 1102, 1103, 1104, 1105, 1106, 1107, 1108, 1109]
Variable Names ==> Transc_1 ,Transc_2 ,Transc_3 ,Transc_4 ,Transc_5 ,Transc_6 ,Transc_7 ,Transc_8 ,Transc_9 ,Transc_10 ,Transc_11 ,Transc_12 ,Transc_13 ,Transc_14 ,Transc_15 ,Transc_16 ,Transc_17 ,Transc_18 ,Transc_19 ,Transc_20 ,Transc_21 ,Transc_22 ,Transc_23 ,Transc_24 ,Transc_25 ,Transc_26 ,Transc_27 ,Transc_28 ,Transc_29 ,Transc_30 ,Transc_31 ,Transc_32 ,Transc_33 ,Transc_34 ,Transc_35 ,Transc_36 ,Transc_37 ,Transc_38 ,Transc_39 ,Transc_40 ,

16==>[1237, 1238, 1239, 1240, 1241, 1242, 1243, 1244]
Variable Names ==> SNAP_19 ,SNAP_20 ,SNAP_21 ,SNAP_22 ,SNAP_23 ,SNAP_24 ,SNAP_25 ,SNAP_26 ,

45==>[1365, 1400, 1401, 1402, 1403, 1404, 1405, 1406, 1407, 1408, 1409, 1410, 1411, 1412, 1413, 1414, 1415, 1417, 1430]
Variable Names ==> TDE_Spell_name ,TDE_Arit_oral_1 ,TDE_Arit_oral_2 ,TDE_Arit_oral_3 ,TDE_Arit_1 ,TDE_Arit_2 ,TDE_Arit_3 ,TDE_Arit_4 ,TDE_Arit_5 ,TDE_Arit_6 ,TDE_Arit_7 ,TDE_Arit_8 ,TDE_Arit_9 ,TDE_Arit_10 ,TDE_Arit_11 ,TDE_Arit_12

,TDE_Arit_13 ,TDE_Arit_15 ,TDE_Arit_28 ,

44==>[1416, 1418, 1419, 1420, 1421, 1422, 1423, 1424, 1425, 1426, 1427, 1428, 1429, 1431, 1432, 1433, 1434, 1435, 1436, 1437]
Variable Names ==> TDE_Arit_14 ,TDE_Arit_16 ,TDE_Arit_17 ,TDE_Arit_18 ,TDE_Arit_19 ,TDE_Arit_20 ,TDE_Arit_21 ,TDE_Arit_22 ,TDE_Arit_23 ,TDE_Arit_24 ,TDE_Arit_25 ,TDE_Arit_26 ,TDE_Arit_27 ,TDE_Arit_29 ,TDE_Arit_30 ,TDE_Arit_31 ,TDE_Arit_32 ,TDE_Arit_33 ,TDE_Arit_34 ,TDE_Arit_35 ,

38==>[1438, 1439, 1440, 1441, 1442, 1443, 1444, 1445, 1446, 1447, 1448, 1449, 1450, 1451, 1452, 1453, 1454, 1455, 1456, 1457, 1458, 1459, 1460, 1461, 1462, 1463, 1464, 1465, 1466, 1467, 1468, 1469, 1470, 1471, 1472, 1473, 1474, 1475, 1476, 1477, 1478, 1479, 1480, 1481, 1482, 1483, 1484, 1485, 1486, 1487, 1488, 1489, 1490, 1491, 1492, 1493, 1494, 1495, 1496, 1497]
Variable Names ==> LPI_Reg_01 ,LPI_Reg_02 ,LPI_Reg_03 ,LPI_Reg_04 ,LPI_Reg_05 ,LPI_Reg_06 ,LPI_Reg_07 ,LPI_Reg_08 ,LPI_Reg_09 ,LPI_Reg_10 ,LPI_Reg_11 ,LPI_Reg_12 ,LPI_Reg_13 ,LPI_Reg_14 ,LPI_Reg_15 ,LPI_Reg_16 ,LPI_Reg_17 ,LPI_Reg_18 ,LPI_Reg_19 ,LPI_Reg_20 ,LPI_Irreg_01 ,LPI_Irreg_02 ,LPI_Irreg_03 ,LPI_Irreg_04 ,LPI_Irreg_05 ,LPI_Irreg_06 ,LPI_Irreg_07 ,LPI_Irreg_08 ,LPI_Irreg_09 ,LPI_Irreg_10 ,LPI_Irreg_11 ,LPI_Irreg_12 ,LPI_Irreg_13 ,LPI_Irreg_14 ,LPI_Irreg_15 ,LPI_Irreg_16 ,LPI_Irreg_17 ,LPI_Irreg_18 ,LPI_Irreg_19 ,LPI_Irreg_20 ,LPI_Pseud_01 ,LPI_Pseud_02 ,LPI_Pseud_03 ,LPI_Pseud_04 ,LPI_Pseud_05 ,LPI_Pseud_06 ,LPI_Pseud_07 ,LPI_Pseud_08 ,LPI_Pseud_09 ,LPI_Pseud_10 ,LPI_Pseud_11 ,LPI_Pseud_12 ,LPI_Pseud_13 ,LPI_Pseud_14 ,LPI_Pseud_15 ,LPI_Pseud_16 ,LPI_Pseud_17 ,LPI_Pseud_18 ,LPI_Pseud_19 ,LPI_Pseud_20 ,

8==>[1498, 1499, 1500, 1501, 1502, 1503, 1504, 1505, 1506, 1507, 1508, 1509, 1510, 1511, 1512, 1513, 1514, 1515, 1516, 1517, 1518, 1519, 1520, 1521, 1522, 1523, 1524, 1525, 1526, 1527, 1528, 1529, 1530, 1531, 1532, 1533]
Variable Names ==> Raven_A_1 ,Raven_A_2 ,Raven_A_3 ,Raven_A_4 ,Raven_A_5 ,Raven_A_6 ,Raven_A_7 ,Raven_A_8 ,Raven_A_9 ,Raven_A_10 ,Raven_A_11 ,Raven_A_12 ,Raven_AB_1 ,Raven_AB_2 ,Raven_AB_3 ,Raven_AB_4 ,Raven_AB_5 ,Raven_AB_6 ,Raven_AB_7 ,Raven_AB_8 ,Raven_AB_9 ,Raven_AB_10 ,Raven_AB_11 ,Raven_AB_12 ,Raven_B_1 ,Raven_B_2 ,Raven_B_3 ,Raven_B_4 ,Raven_B_5 ,Raven_B_6 ,Raven_B_7 ,Raven_B_8 ,Raven_B_9 ,Raven_B_10 ,Raven_B_11 ,Raven_B_12

G.4 Dataset 762

Leader variables 0==>Age_months
3==>RavenNovo_junto_Adulto

5==>ParaCOM_QI
11==>IMO_RD
12==>VP
21==>Arranj_fig_Pond
28==>Codigos_Pond
35==>Nine_Relative_handedness
38==>Fluenc_Arit_CalcPulados
42==>Nscreener_Simb_Made
44==>Nscreener_Nsimb_Made
46==>Reading_Fluency_Time
47==>Reading_Fluency_LP
56==>Multidigits_T_Adicao
64==>Supressao_Fon_30
71==>RAN_2_erros
74==>CBCL_SomaticComplaints_SN
83==>P_Digits_1digitcomparison
84==>SNAP_Mean_ADHD_inattention
98==>RAVLT_LB_1
159==>Transc81_08_answ
237==>NumRead_5
287==>NumRead_R_28
290==>Add_S_03
303==>Add_S_04_answ
360==>Sub_S_07_answ
448==>CB_bath
450==>CB_car
453==>CB_fridge
464==>CB_People_House
489==>OV_CB_ref
491==>OV_CB_iy
537==>Pho_Elis_06
584==>Est_median_2
894==>Banuca9_RA_14
992==>NM_index_nose_eyes_open
1014==>Corsi_F_6_1
1018==>Corsi_F_8_1
1067==>Transc_1
1244==>CBCL_3
1362==>TDE_Spell_name

1363==>TDE_Spell_1
1435==>LPI_Reg_01
1495==>Raven_A_1

List of cluster variables

43==>[0, 1, 2, 70, 76, 78, 82, 513, 514, 521, 750, 753]
Variable Names ==> Age_months ,Age_years ,Grade ,RAN_1_erros ,Add_S_Time ,Sub_S_Time ,P_Dots_ref32 ,MAQ_DC_01 ,MAQ_DC_02 ,MAQ_MC_01 ,Rey_rec2_4 ,Rey_rec2_7 ,

5==>[3, 4, 6, 7, 8, 9, 10, 13, 14, 15, 16, 17, 18, 19, 20, 22, 23, 24, 25, 26, 507, 539, 851, 859, 1001, 1002]

Variable Names ==>
RavenNovo_junto_Adulto ,Inteligencia_FINAL_juntos ,Vocab_PP_revisado ,Cubos_PP_revisado ,QI_T ,CV ,OP ,QI_V ,QI_E ,Semel_PP_Triagem ,Digitos_Pond ,Semelh_Pond ,Inform_Pond ,Compreen_Pon ,Compl_fig_Pond ,Armar_obj_Pond ,Racioc_Matric_Pon ,Conc_Fig_Pond ,Arit_Pond ,Seq_N_Let_Pon ,MAQ_GM_03 ,Pho_Elis_08 ,Banuca7_RN_7 ,Banuca7_RN_7_resp ,School_type ,wisc_reduzido_final ,

19==>[5, 234, 235, 236, 239, 241, 242, 263, 317, 332, 1004, 1005, 1006, 1007, 1008, 1009, 1010, 1011, 1012, 1013, 1020, 1021, 1022, 1023, 1024, 1025, 1026, 1027, 1036, 1037, 1038, 1039, 1040, 1041, 1042, 1043, 1044, 1045, 1052, 1053, 1054, 1055, 1056, 1057]

Variable Names ==>
ParaCOM_QI ,NumRead_2 ,NumRead_3 ,NumRead_4 ,NumRead_7 ,NumRead_9 ,NumRead_10 ,NumRead_R_3 ,Add_C_06 ,Add_C_06_answ ,Corsi_F_1_1 ,Corsi_F_1_2 ,Corsi_F_2_1 ,Corsi_F_2_2 ,Corsi_F_3_1 ,Corsi_F_3_2 ,Corsi_F_4_1 ,Corsi_F_4_2 ,Corsi_F_5_1 ,Corsi_F_5_2 ,Corsi_B_1_1 ,Corsi_B_1_2 ,Corsi_B_2_1 ,Corsi_B_2_2 ,Corsi_B_3_1 ,Corsi_B_3_2 ,Corsi_B_4_1 ,Corsi_B_4_2 ,Dspan_F_1_1 ,Dspan_F_1_2 ,Dspan_F_2_1 ,Dspan_F_2_2 ,Dspan_F_3_1 ,Dspan_F_3_2 ,Dspan_F_4_1 ,Dspan_F_4_2 ,Dspan_F_5_1 ,Dspan_F_5_2 ,Dspan_B_1_1 ,Dspan_B_1_2 ,Dspan_B_2_1 ,Dspan_B_2_2 ,Dspan_B_3_1 ,Dspan_B_3_2 ,

4==>[11, 30, 37, 40, 41, 48, 55, 58, 59, 66, 92, 93, 94, 95, 102, 111, 248, 252, 255, 256, 257, 258, 259, 260, 335, 347, 349, 387, 391, 392, 394, 395, 427, 531, 533, 534, 538, 540, 542, 543, 544, 545, 547, 549, 554, 561, 562, 563, 580, 624, 644, 647, 656, 660, 664, 665, 666, 667, 669, 673, 676, 677, 681, 694, 695, 700, 701, 703, 704, 714, 728, 740, 745, 756, 757, 763, 771, 775, 777, 778, 779, 784, 785, 786, 796, 797, 798, 800, 806, 808, 816, 824, 829, 841, 850, 861, 871, 874, 881, 882, 884, 885, 887, 890, 896, 898, 908, 909, 911, 912, 914, 916, 926, 928, 931, 935, 944, 953]

Variable Names ==>
IMO_RD ,Cancel_Pond ,Fluenc_Arit_CalcFeitos ,Fluenc_Arit_Erros ,Fluenc_Arit_Corretas ,Reading_Fluency_Errors ,Numb_Read_81 ,Multidigits_T_Mult ,Warring_multiplicacao ,RAN_1 ,Five_Points_erros ,RAVLT_LA_1 ,RAVLT_LA_2 ,RAVLT_LA_3 ,Stroop_Vic_Color ,Verbal_Fluency_An_Repetition ,NumRead_16 ,NumRead_20 ,NumRead_23 ,NumRead_24
,NumRead_25 ,NumRead_26 ,NumRead_27 ,NumRead_28 ,Add_C_09_answ ,Sub_S_06 ,Sub_S_08 ,Sub_C_07_answ ,Sub_C_11_answ ,Sub_C_12_answ ,Sub_C_14_answ ,Sub_C_15_answ ,Prob_04 ,LPI_Pseud_Porcentagem ,Pho_Elis_02 ,Pho_Elis_03 ,Pho_Elis_07 ,Pho_Elis_09 ,Pho_Elis_11 ,Pho_Elis_12 ,Pho_Elis_13 ,Pho_Elis_14 ,Pho_Elis_16 ,Pho_Elis_18 ,Pho_Elis_23 ,Five_Dig_Count_E ,Five_Dig_Choos_E ,Five_Dig_Switch_E ,Rey_copy_16 ,TDE_Read_2 ,TDE_Read_22 ,TDE_Read_25 ,TDE_Read_34 ,TDE_Read_38 ,TDE_Read_42 ,TDE_Read_43 ,TDE_Read_44 ,TDE_Read_45 ,TDE_Read_47 ,TDE_Read_51 ,TDE_Read_54 ,TDE_Read_55 ,TDE_Read_59 ,Orient_2 ,Orient_3 ,Orient_8 ,Orient_9 ,Orient_11 ,Orient_12 ,Fgnosia_RH_10 ,Fgnosia_LH_12 ,Rey_rec1_12 ,Rey_rec1_17 ,Rey_rec2_10 ,Rey_rec2_11 ,Rey_rec2_17 ,Banuca2_AS_1 ,Banuca2_AS_5 ,Banuca2_AS_7 ,Banuca2_AS_8 ,Banuca2_AS_1_resp ,Banuca2_AS_6_resp ,Banuca2_AS_7_resp ,Banuca2_AS_8_resp ,Banuca4_SS_4 ,Banuca4_SS_5 ,Banuca4_SS_6 ,Banuca4_SS_8 ,Banuca4_SS_6_resp ,Banuca4_SS_8_resp ,Banuca5_LN_8 ,Banuca5_LN_8_resp ,Banuca6_CN_5 ,Banuca6_CN_7_resp ,Banuca7_RN_6 ,Banuca8_CM_1 ,Banuca8_CM_1_resp ,Banuca8_CM_4_resp ,Banuca9_RA_1 ,Banuca9_RA_2 ,Banuca9_RA_4 ,Banuca9_RA_5 ,Banuca9_RA_7 ,Banuca9_RA_10 ,Banuca9_RA_1_resp ,Banuca9_RA_3_resp ,Banuca9_RA_13_resp ,Banuca9_RA_14_resp ,Fgnosia_RH_visivel ,Fgnosia_RH_escondido ,Fgnosia_LH_visivel ,Fgnosia_LH_dois_dedos ,Num_Line_Paper_8 ,Num_Line_Paper_90 ,Num_Line_Paper_3 ,Num_Line_Paper_96
,Num_Line_Paper_Ajust_Linear ,Span_PP_8 ,

3==>[12, 27, 29, 516, 765, 772, 773, 774, 776, 781, 783, 789, 791, 792, 793, 794, 795, 801, 802, 803, 804, 805, 811, 812, 813, 814, 819, 823, 825, 826, 827, 828, 830, 832, 835, 837, 838, 840, 844, 846, 847, 848, 849, 854, 857, 860, 872, 873, 878, 902, 906, 910, 945]
Variable Names ==> VP ,Racioc_Palavras_Pond ,Proc_Simb_Pond ,MAQ_DC_04 ,Banuca1_CP_1 ,Banuca2_AS_2 ,Banuca2_AS_3 ,Banuca2_AS_4 ,Banuca2_AS_6 ,Banuca2_AS_3_resp ,Banuca2_AS_5_resp ,Banuca3_C_3 ,Banuca3_C_5 ,Banuca3_C_6 ,Banuca4_SS_1 ,Banuca4_SS_2 ,Banuca4_SS_3 ,Banuca4_SS_1_resp ,Banuca4_SS_2_resp ,Banuca4_SS_3_resp ,Banuca4_SS_4_resp ,Banuca4_SS_5_resp ,Banuca5_LN_3 ,Banuca5_LN_4

,Banuca5_LN_5 ,Banuca5_LN_6 ,Banuca5_LN_3_resp ,Banuca5_LN_7_resp ,Banuca6_CN_1 ,Banuca6_CN_2 ,Banuca6_CN_3 ,Banuca6_CN_4 ,Banuca6_CN_6 ,Banuca6_CN_8 ,Banuca6_CN_1_resp ,Banuca6_CN_3_resp ,Banuca6_CN_4_resp ,Banuca6_CN_6_resp ,Banuca6_CN_10_resp ,Banuca7_RN_2 ,Banuca7_RN_3 ,Banuca7_RN_4 ,Banuca7_RN_5 ,Banuca7_RN_2_resp ,Banuca7_RN_5_resp ,Banuca7_RN_8_resp ,Banuca8_CM_2_resp ,Banuca8_CM_3_resp ,Banuca8_CM_8_resp ,Banuca9_RA_7_resp ,Banuca9_RA_11_resp ,Banuca9_RA_15_resp ,Num_Line_Paper_Ajust_Logaritmic ,

6==>[21, 31, 32, 33, 34, 565, 566, 567, 570, 571, 572, 573, 574, 575, 577, 578, 579, 581, 582, 733, 739, 741, 742, 747, 748, 751, 759, 990]

Variable Names ==>
Arranj_fig_Pond ,Nine_RH_mean ,Nine_DH_mean ,Nine_LH_mean ,Nine_NDH_mean ,Rey_copy_1 ,Rey_copy_2 ,Rey_copy_3 ,Rey_copy_6 ,Rey_copy_7 ,Rey_copy_8 ,Rey_copy_9 ,Rey_copy_10 ,Rey_copy_11 ,Rey_copy_13 ,Rey_copy_14 ,Rey_copy_15 ,Rey_copy_17 ,Rey_copy_18 ,Rey_rec1_5 ,Rey_rec1_11 ,Rey_rec1_13 ,Rey_rec1_14 ,Rey_rec2_1 ,Rey_rec2_2 ,Rey_rec2_5 ,Rey_rec2_13 ,NM_Fgnosia_LH_3 ,

8==>[28, 36, 110, 268, 337, 338, 340, 341, 348, 382, 383, 390, 402, 403, 405, 406, 410, 445, 618, 619, 621, 628, 674, 782, 818, 821, 831, 834, 855, 913, 915, 918, 919]

Variable Names ==>
Codigos_Pond ,fracao_w ,wrsquared ,NumRead_R_8 ,Add_C_11_answ ,Add_C_12_answ ,Add_C_14_answ ,Add_C_15_answ ,Sub_S_07 ,Sub_C_02_answ ,Sub_C_03_answ ,Sub_C_10_answ ,Mul_S_07_answ ,Mul_S_08_answ ,Mul_S_10_answ ,Mul_S_11_answ ,Mul_S_15_answ ,Prob_R_10 ,Digits_arcsine_4 ,Digits_arcsine_6 ,Digits_arcsine_8 ,TDE_Read_6 ,TDE_Read_52 ,Banuca2_AS_4_resp ,Banuca5_LN_2_resp ,Banuca5_LN_5_resp ,Banuca6_CN_7 ,Banuca6_CN_10 ,Banuca7_RN_3_resp ,Fgnosia_RH_dois_dedos ,Fgnosia_LH_escondido ,Fgnosias_RLH_escondido ,Fgnosias_RLH_dois_dedos ,

26==>[35, 77, 79, 80, 81, 233, 244, 272, 273, 274, 275, 277, 278, 279, 280, 281, 282, 283, 284, 285, 286, 359, 404, 407, 439, 505, 515, 522, 627, 646, 866, 879, 966]
Variable Names ==> Nine_Relative_handedness ,Add_C_Time ,Sub_C_Time ,Mul_S_Time ,Mul_C_Time ,NumRead_1 ,NumRead_12 ,NumRead_R_12 ,NumRead_R_13 ,NumRead_R_14 ,NumRead_R_15 ,NumRead_R_18 ,NumRead_R_19 ,NumRead_R_20 ,NumRead_R_21 ,NumRead_R_22 ,NumRead_R_23 ,NumRead_R_24 ,NumRead_R_25 ,NumRead_R_26 ,NumRead_R_27 ,Sub_S_06_answ ,Mul_S_09_answ ,Mul_S_12_answ ,Prob_R_4 ,MAQ_GM_01 ,MAQ_DC_03 ,MAQ_MC_02 ,TDE_Read_5 ,TDE_Read_24 ,Banuca8_CM_6 ,Banuca8_CM_9_resp ,mult_comp_dp4 ,

12==>[38, 39, 63, 91, 112, 113, 114, 116, 118, 119, 121, 131, 133, 134, 135, 138, 139, 142, 146, 147, 149, 150, 151, 152, 153, 154, 155, 156, 158, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169, 170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 180, 181, 182, 183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194, 195, 196, 197, 198, 199, 200, 201, 202, 203, 204, 205, 206, 207, 208, 209, 210, 211, 212, 213, 214, 215, 216, 217, 218, 219, 220, 221, 222, 223, 224, 225, 226, 227, 228, 229, 230, 231, 232, 393, 399, 506, 517, 519, 528, 711, 724, 726, 766, 767, 768, 787, 790, 822, 839, 856, 858, 875, 880, 888, 904, 951, 991, 1107, 1108, 1109, 1110, 1111, 1112, 1113, 1114, 1115, 1116, 1117, 1118, 1119, 1120, 1121, 1122, 1123, 1124, 1125, 1126, 1127, 1128, 1129, 1130, 1131, 1132, 1133, 1134, 1135, 1136, 1137, 1138, 1139, 1140, 1141, 1142, 1143, 1144, 1145, 1146, 1147, 1148, 1149, 1150, 1151, 1152, 1153, 1154, 1155, 1156, 1157, 1158, 1159, 1160, 1161, 1162, 1163, 1164, 1165, 1166, 1167, 1168, 1169, 1170, 1171, 1172, 1173, 1174, 1175, 1176, 1177, 1178, 1179, 1180, 1181, 1182, 1183, 1184, 1185, 1186, 1187]

Variable Names ==>
Fluenc_Arit_CalcPulados ,Fluenc_Arit_Tempo ,Repet_Pseudo_15 ,Five_Points_repet ,Transc_R_1 ,Transc_R_2 ,Transc_R_3 ,Transc_R_5 ,Transc_R_7 ,Transc_R_8 , Transc_R_10 ,Transc_R_20 ,Transc_R_22 ,Transc_R_23 ,Transc_R_24 ,Transc_R_27 ,Transc_R_28 ,Transc_R_31 ,Transc_R_35 ,Transc_R_36 ,Transc_R_38 ,Transc_R_39 ,Transc_R_40 ,Transc81_01_answ ,Transc81_02_answ ,Transc81_03_answ ,Transc81_04_answ ,Transc81_05_answ ,Transc81_07_answ ,Transc81_09_answ ,Transc81_10_answ ,Transc81_11_answ ,Transc81_12_answ ,Transc81_13_answ ,Transc81_14_answ ,Transc81_15_answ ,Transc81_16_answ ,Transc81_17_answ ,Transc81_18_answ ,Transc81_19_answ ,Transc81_20_answ ,Transc81_21_answ ,Transc81_22_answ ,Transc81_23_answ ,Transc81_24_answ ,Transc81_25_answ ,Transc81_26_answ ,Transc81_27_answ ,Transc81_28_answ ,Transc81_29_answ ,Transc81_30_answ ,Transc81_31_answ ,Transc81_32_answ ,Transc81_33_answ ,Transc81_34_answ ,Transc81_35_answ ,Transc81_36_answ ,Transc81_37_answ ,Transc81_38_answ ,Transc81_39_answ ,Transc81_40_answ ,Transc81_41_answ ,Transc81_42_answ ,Transc81_43_answ ,Transc81_44_answ ,Transc81_45_answ ,Transc81_46_answ ,Transc81_47_answ ,Transc81_48_answ ,Transc81_49_answ ,Transc81_50_answ ,Transc81_51_answ ,Transc81_52_answ ,Transc81_53_answ ,Transc81_54_answ ,Transc81_55_answ ,Transc81_56_answ ,Transc81_57_answ ,Transc81_58_answ ,Transc81_59_answ ,Transc81_60_answ ,Transc81_61_answ ,Transc81_62_answ ,Transc81_63_answ ,Transc81_64_answ ,Transc81_65_answ ,Transc81_66_answ ,Transc81_67_answ ,Transc81_68_answ ,Transc81_69_answ ,Transc81_70_answ ,Transc81_71_answ ,Transc81_72_answ ,Transc81_73_answ ,Transc81_74_answ ,Transc81_75_answ ,Transc81_76_answ ,Transc81_77_answ ,Transc81_78_answ ,Transc81_79_answ ,Transc81_80_answ ,Transc81_81_answ ,Sub_C_13_answ ,Mul_S_04_answ ,MAQ_GM_02 ,MAQ_WC_01 ,MAQ_WC_03 ,MAQ_HW_04, Fgnosia_RH_7,Fgnosia_LH_8 ,Fgnosia_LH_10 ,Banuca1_CP_2,

Banuca1_CP_3 ,Banuca1_CP_4 ,Banuca3_C_1 ,Banuca3_C_4 ,Banuca5_LN_6_resp ,Banuca6_CN_5_resp ,Banuca7_RN_4_resp ,Banuca7_RN_6_resp ,Banuca8_CM_5_resp ,Banuca8_CM_10_resp ,Banuca9_RA_8 ,Banuca9_RA_9_resp ,Span_PP_6 ,NM_Estereotipias ,Transc81_01 ,Transc81_02 ,Transc81_03 ,Transc81_04 ,Transc81_05 ,Transc81_06 ,Transc81_07 ,Transc81_08 ,Transc81_09 ,Transc81_10 ,Transc81_11 ,Transc81_12 ,Transc81_13 ,Transc81_14 ,Transc81_15 ,Transc81_16 ,Transc81_17 ,Transc81_18 ,Transc81_19 ,Transc81_20 ,Transc81_21 ,Transc81_22 ,Transc81_23 ,Transc81_24 ,Transc81_25 ,Transc81_26 ,Transc81_27 ,Transc81_28 ,Transc81_29 ,Transc81_30 ,Transc81_31 ,Transc81_32 ,Transc81_33 ,Transc81_34 ,Transc81_35 ,Transc81_36 ,Transc81_37 ,Transc81_38 ,Transc81_39 ,Transc81_40 ,Transc81_41 ,Transc81_42 ,Transc81_43 ,Transc81_44 ,Transc81_45 ,Transc81_46 ,Transc81_47 ,Transc81_48 ,Transc81_49 ,Transc81_50 ,Transc81_51 ,Transc81_52 ,Transc81_53 ,Transc81_54 ,Transc81_55 ,Transc81_56 ,Transc81_57 ,Transc81_58 ,Transc81_59 ,Transc81_60 ,Transc81_61 ,Transc81_62 ,Transc81_63 ,Transc81_64 ,Transc81_65 ,Transc81_66 ,Transc81_67 ,Transc81_68 ,Transc81_69 ,Transc81_70 ,Transc81_71 ,Transc81_72 ,Transc81_73 ,Transc81_74 ,Transc81_75 ,Transc81_76 ,Transc81_77 ,Transc81_78 ,Transc81_79 ,Transc81_80 ,Transc81_81 ,

44==>[42, 43, 52, 53, 54, 465, 524, 731, 749, 886, 901]
Variable Names ==> Nscreener_Simb_Made ,Nscreener_Simb_TC ,Five_Dig_Switch_RT ,Five_Dig_Inhibit_RT ,Five_Dig_Flexib_RT ,CB_People_bedroom ,MAQ_MC_04 ,Rey_rec1_3 ,Rey_rec2_3 ,Banuca9_RA_6 ,Banuca9_RA_6_resp ,

13==>[44, 45, 60, 61, 67, 68, 69, 88, 90, 96, 97, 100, 101, 103, 104, 105, 157, 511, 512, 569, 770, 780, 810, 836, 842, 843, 845, 900, 903, 905, 993]
Variable Names ==> Nscreener_Nsimb_Made ,Nscreener_Nsimb_TC ,Warring_operacoes ,Warring_cotidiano ,RAN_2 ,RAN_3 ,RAN_4 ,Verbal_Fluency_An_Corrects ,Five_Points_orig ,RAVLT_LA_4 ,RAVLT_LA_5 ,RAVLT_LA_7 ,RAVLT_Reconhec ,Stroop_Vic_ColorW ,Stroop_Vic_Incongr ,Stroop_Vic_Interf ,Transc81_06_answ ,MAQ_EC_03 ,MAQ_EC_04 ,Rey_copy_5 ,Banuca1_CP_6 ,Banuca2_AS_2_resp ,Banuca5_LN_2 ,Banuca6_CN_2_resp ,Banuca6_CN_8_resp ,Banuca6_CN_9_resp ,Banuca7_RN_1 ,Banuca9_RA_5_resp ,Banuca9_RA_8_resp ,Banuca9_RA_10_resp ,NM_index_nose_eyes_close ,

17==>[46, 89, 117, 120, 122, 123, 124, 125, 126, 127, 128, 129, 130, 132, 136, 137, 140, 141, 143, 144, 145, 148, 525, 526, 527, 743, 758, 820, 870, 893, 925, 960, 969]

Variable Names ==>
Reading_Fluency_Time ,Verbal_Fluency_An_Errors ,Transc_R_6 ,Transc_R_9 ,Transc_R_11 ,Transc_R_12 ,Transc_R_13 ,Transc_R_14 ,Transc_R_15 ,Transc_R_16 ,Transc_R_17 ,Transc_R_18 ,Transc_R_19 ,Transc_R_21 ,Transc_R_25 ,Transc_R_26 ,Transc_R_29 ,Transc_R_30 ,Transc_R_32 ,Transc_R_33 ,Transc_R_34 ,Transc_R_37 ,MAQ_HW_01

,MAQ_HW_02 ,MAQ_HW_03 ,Rey_rec1_15 ,Rey_rec2_12 ,Banuca5_LN_4_resp , Banuca8_CM_10 ,Banuca9_RA_13 ,Num_Line_Paper_64 ,mult_comp_med7 ,mult_comp_dp7 ,

7==>[47, 49, 50, 51, 62, 106, 107, 108, 109, 299, 318, 320, 322, 323, 325, 326, 350, 352, 353, 362, 363, 364, 365, 366, 367, 368, 369, 370, 371, 373, 374, 375, 376, 377, 378, 379, 380, 384, 388, 389, 396, 401, 408, 409, 419, 423, 532, 535, 555, 658, 662, 663, 670, 675, 678, 680, 682, 683, 684, 685, 686, 687, 688, 689, 690, 691, 692, 712, 713, 715, 716, 719, 720, 721, 727, 754, 799, 815, 833, 852, 862, 863, 865, 867, 868, 883, 889, 891, 899, 952, 954, 956, 957, 958, 959, 961, 962, 963, 964, 965, 967, 968, 970, 971, 972, 973, 974, 975, 976, 977, 978, 979, 980, 981]
Variable Names ==> Reading_Fluency_LP ,Five_Dig_Read_RT ,Five_Dig_Cout_RT ,Five_Dig_Choos_RT ,Leit_Pseudo_40 ,SRT_mean ,SRT_sd ,SRT_min ,SRT_max ,Add_S_12 ,Add_C_07 ,Add_C_09 ,Add_C_11 ,Add_C_12 ,Add_C_14 ,Add_C_15 ,Sub_S_09 ,Sub_S_11 ,Sub_S_12 ,Sub_S_09_answ ,Sub_S_10_answ ,Sub_S_11_answ ,Sub_S_12_answ ,Sub_C_01 ,Sub_C_02 ,Sub_C_03 ,Sub_C_04 ,Sub_C_05 ,Sub_C_06 ,Sub_C_08 ,Sub_C_09 ,Sub_C_10 ,Sub_C_11 ,Sub_C_12 ,Sub_C_13 ,Sub_C_14 ,Sub_C_15 ,Sub_C_04_answ ,Sub_C_08_answ ,Sub_C_09_answ ,Mul_S_01_answ ,Mul_S_06_answ ,Mul_S_13_answ ,Mul_S_14_answ ,Mul_C_09_answ ,Mul_C_13_answ ,Pho_Elis_01 ,Pho_Elis_04 ,Pho_Elis_24 ,TDE_Read_36 ,TDE_Read_40 ,TDE_Read_41 ,TDE_Read_48 ,TDE_Read_53 ,TDE_Read_56 ,TDE_Read_58 , TDE_Read_60 ,TDE_Read_61 ,TDE_Read_62 ,TDE_Read_63 ,TDE_Read_64 ,TDE_Read_65 ,TDE_Read_66 ,TDE_Read_67 ,TDE_Read_68 ,TDE_Read_69 ,TDE_Read_70 ,Fgnosia_RH_8 ,Fgnosia_RH_9 ,Fgnosia_RH_11 ,Fgnosia_RH_12 ,Fgnosia_LH_3 ,Fgnosia_LH_4 ,Fgnosia_LH_5 ,Fgnosia_LH_11 ,Rey_rec2_8 ,Banuca4_SS_7 ,Banuca5_LN_7 ,Banuca6_CN_9 ,Banuca7_RN_8 ,Banuca8_CM_2 ,Banuca8_CM_3 ,Banuca8_CM_5 ,Banuca8_CM_7 ,Banuca8_CM_8 ,Banuca9_RA_3 ,Banuca9_RA_9 ,Banuca9_RA_11 ,Banuca9_RA_4_resp ,Span_PP_7 ,mult_comp_med1 ,mult_comp_med3 ,mult_comp_med4 ,mult_comp_med5 ,mult_comp_med6 ,mult_comp_med8 ,mult_comp_med9 ,mult_comp_dp1 ,mult_comp_dp2 ,mult_comp_dp3 ,mult_comp_dp5 ,mult_comp_dp6 ,mult_comp_dp8 ,mult_comp_dp9 ,mult_comp_acc1 ,mult_comp_acc2 ,mult_comp_acc3 ,mult_comp_acc4 ,mult_comp_acc5 ,mult_comp_acc6 ,mult_comp_acc7 ,mult_comp_acc8 ,mult_comp_acc9 ,Ideb ,

39==>[56, 57, 266, 267, 269, 276, 297, 309, 314, 319, 329, 334, 386, 400, 431, 443, 509, 510, 876, 892, 895, 907]
Variable Names ==> Multidigits_T_Adicao ,Multidigits_T_Sub ,NumRead_R_6 ,Num-Read_R_7 ,NumRead_R_9 ,NumRead_R_17 ,Add_S_10 ,Add_S_10_answ ,Add_C_03 ,Add_C_08 ,Add_C_03_answ ,Add_C_08_answ ,Sub_C_06_answ ,Mul_S_05_answ ,Prob_08 ,Prob_R_8 ,MAQ_EC_01 ,MAQ_EC_02 ,Banuca8_CM_6_resp ,Banuca9_RA_12

,Banuca9_RA_15 ,Banuca9_RA_12_resp ,

10==>[64, 65, 529, 530, 558, 623, 625, 626, 629, 630, 631, 632, 633, 635, 636, 637, 638, 639, 640, 642, 643, 645, 648, 649, 650, 651, 652, 653, 654, 655, 657, 659, 661, 671, 672, 679, 737]
Variable Names ==>
Supressao_Fon_30 ,Repet_Pseudo_40 ,LPI_Reg_Porcentagem ,LPI_Irreg_Porcentagem ,Pho_Elis_27 ,TDE_Read_1 ,TDE_Read_3 ,TDE_Read_4 ,TDE_Read_7 ,TDE_Read_8 ,TDE_Read_9 ,TDE_Read_10 ,TDE_Read_11 ,TDE_Read_13 ,TDE_Read_14 ,TDE_Read_15 ,TDE_Read_16 ,TDE_Read_17 ,TDE_Read_18 ,TDE_Read_20 ,TDE_Read_21 ,TDE_Read_23 ,TDE_Read_26 ,TDE_Read_27 ,TDE_Read_28 ,TDE_Read_29 ,TDE_Read_30 ,TDE_Read_31 ,TDE_Read_32 ,TDE_Read_33 ,TDE_Read_35 ,TDE_Read_37 ,TDE_Read_39 ,TDE_Read_49 ,TDE_Read_50 ,TDE_Read_57 ,Rey_rec1_9 ,

31==>[71, 72, 73, 115, 261, 583, 593, 599, 693, 696, 697, 698, 699, 705, 706, 707, 708, 709, 710, 717, 718, 722, 723, 725, 769, 817, 853, 917, 946, 947, 948, 949, 950, 1000]
Variable Names ==> RAN_2_erros ,RAN_3_erros ,RAN_4_erros ,Transc_R_4 ,Num-Read_R_1 ,Est_median_1 ,Est_median_56 ,Est_RT_mean_5 ,Orient_1 ,Orient_4 ,Orient_5 ,Orient_6 ,Orient_7 ,Fgnosia_RH_1 ,Fgnosia_RH_2 ,Fgnosia_RH_3 ,Fg-nosia_RH_4 ,Fgnosia_RH_5 ,Fgnosia_RH_6 ,Fgnosia_LH_1 ,Fgnosia_LH_2 ,Fgnosia_LH_6 ,Fgnosia_LH_7 ,Fgnosia_LH_9 ,Banuca1_CP_5 ,Banuca5_LN_1_resp ,Banuca7_RN_1_resp ,Fgnosias_RLH_visivel ,Span_PP_1 ,Span_PP_2 ,Span_PP_3 ,Span_PP_4 ,Span_PP_5 ,Sex ,

22==>[74, 75, 702, 1242, 1243, 1246, 1247, 1250, 1252, 1253, 1254, 1255, 1258, 1259, 1260, 1265, 1266, 1268, 1270, 1271, 1272, 1273, 1274, 1275, 1276, 1279, 1281, 1283, 1285, 1287, 1288, 1289, 1290, 1291, 1292, 1293, 1294, 1295, 1296, 1297, 1298, 1299, 1300, 1301, 1302, 1303, 1304, 1306, 1307, 1308, 1311, 1312, 1313, 1314, 1315, 1317, 1318, 1319, 1320, 1321, 1323, 1324, 1325, 1327, 1328, 1329, 1330, 1331, 1332, 1333, 1335, 1336, 1337, 1339, 1340, 1344, 1345, 1346, 1347, 1348, 1349, 1350, 1351, 1353, 1354, 1355, 1356, 1357, 1358, 1359, 1360, 1361]
Variable Names ==> CBCL_SomaticComplaints_SN ,CBCL_SomaticProblems_SN ,Orient_10 ,CBCL_1 ,CBCL_2 ,CBCL_5 ,CBCL_6 ,CBCL_9 ,CBCL_11 ,CBCL_12 ,CBCL_13 ,CBCL_14 ,CBCL_17 ,CBCL_18 ,CBCL_19 ,CBCL_24 ,CBCL_25 ,CBCL_27 ,CBCL_29 ,CBCL_30 ,CBCL_31 ,CBCL_32 ,CBCL_33 ,CBCL_34 ,CBCL_35 ,CBCL_38 ,CBCL_40 ,CBCL_42 ,CBCL_44 ,CBCL_46 ,CBCL_47 ,CBCL_48 ,CBCL_49 ,CBCL_50 ,CBCL_51 ,CBCL_52 ,CBCL_53 ,CBCL_54 ,CBCL_55 ,CBCL_56_a ,CBCL_56_b ,CBCL_56_c ,CBCL_56_d ,CBCL_56_e ,CBCL_56_f ,CBCL_56_g ,CBCL_56_h ,CBCL_58 ,CBCL_59 ,CBCL_60 ,CBCL_63 ,CBCL_64 ,CBCL_65 ,CBCL_66 ,CBCL_67 ,CBCL_69 ,CBCL_70 ,CBCL_71 ,CBCL_72 ,CBCL_73 ,CBCL_75 ,CBCL_76 ,CBCL_77

,CBCL_79 ,CBCL_80 ,CBCL_81 ,CBCL_82 ,CBCL_83 ,CBCL_84 ,CBCL_85 ,CBCL_87 ,CBCL_88 ,CBCL_89 ,CBCL_91 ,CBCL_92 ,CBCL_96 ,CBCL_97 ,CBCL_98 ,CBCL_99 ,CBCL_100 ,CBCL_101 ,CBCL_102 ,CBCL_103 ,CBCL_105 ,CBCL_106 ,CBCL_107 ,CBCL_108 ,CBCL_109 ,CBCL_110 ,CBCL_111 ,CBCL_112 ,CBCL_113 ,

16==>[83, 607, 608, 609, 610, 611, 612, 613, 614, 615, 616, 617, 620, 622]
Variable Names ==> P_Digits_1digitcomparison ,Digits_error_1 ,Digits_error_2 ,Digits_error_3 ,Digits_error_4 ,Digits_error_6 ,Digits_error_7 ,Digits_error_8 ,Digits_error_9 ,Digits_arcsine_1 ,Digits_arcsine_2 ,Digits_arcsine_3 ,Digits_arcsine_7 ,Digits_arcsine_9 ,

32==>[84, 85, 86, 87, 1216, 1217, 1218, 1219, 1220, 1221, 1222, 1223, 1224, 1225, 1226, 1227, 1228, 1229, 1230, 1231, 1232, 1233, 1234, 1235, 1236, 1237, 1238, 1239, 1240, 1241]

Variable Names ==>
SNAP_Mean_ADHD_inattention ,SNAP_Mean_ADHD_hyperactivity ,SNAP_Mean_ADHD_combined ,SNAP_Mean_ODD ,SNAP_1 ,SNAP_2 ,SNAP_3 ,SNAP_4 ,SNAP_5 ,SNAP_6 ,SNAP_7 ,SNAP_8 ,SNAP_9 ,SNAP_10 ,SNAP_11 ,SNAP_12 ,SNAP_13 ,SNAP_14 ,SNAP_15 ,SNAP_16 ,SNAP_17 ,SNAP_18 ,SNAP_19 ,SNAP_20 ,SNAP_21 ,SNAP_22 ,SNAP_23 ,SNAP_24 ,SNAP_25 ,SNAP_26 ,

14==>[98, 99, 245, 288, 300, 310, 321, 324, 343, 356, 361, 398, 432, 435, 444, 447, 568, 576, 729, 730, 744, 760, 762, 921, 923, 924, 927, 986, 987, 989, 1003]

Variable Names ==>
RAVLT_LB_1 ,RAVLT_LA_6 ,NumRead_13 ,Add_S_01 ,Add_S_01_answ ,Add_S_11_answ ,Add_C_10 ,Add_C_13 ,Sub_S_02 ,Sub_S_03_answ ,Sub_S_08_answ ,Mul_S_03_answ ,Prob_09 ,Prob_12 ,Prob_R_9 ,Prob_R_12 ,Rey_copy_4 ,Rey_copy_12 ,Rey_rec1_1 ,Rey_rec1_2 ,Rey_rec1_16 ,Rey_rec2_14 ,Rey_rec2_16 ,Num_Line_Paper_79 ,Num_Line_Paper_84 ,Num_Line_Paper_61 ,Num_Line_Paper_81 ,NM_Fgnosia_RH_2 ,NM_Fgnosia_RH_3 ,NM_Fgnosia_LH_2 ,preferencia_manual ,

40==>[159, 305, 336, 339, 508, 518, 520, 634, 641, 734, 735, 736, 746, 752, 755, 764, 788, 936, 943, 955, 994, 995]

Variable Names ==>
Transc81_08_answ ,Add_S_06_answ ,Add_C_10_answ ,Add_C_13_answ ,MAQ_GM_04 ,MAQ_WC_02 ,MAQ_WC_04 ,TDE_Read_12 ,TDE_Read_19 ,Rey_rec1_6 ,Rey_rec1_7 ,Rey_rec1_8 ,Rey_rec1_18 ,Rey_rec2_6 ,Rey_rec2_9 ,Rey_rec2_18 ,Banuca3_C_2 ,Num_Line_Paper_52 ,Num_Line_Paper_72 ,mult_comp_med2 ,NM_Marcha_unip_D

,NM_Marcha_unip_E ,

27==>[237, 238, 240, 243, 246, 247, 249, 250, 251, 253, 254, 262, 264, 265, 270, 271, 289, 291, 293, 294, 298, 301, 307, 316, 385, 536, 877]
Variable Names ==> NumRead_5 ,NumRead_6 ,NumRead_8 ,NumRead_11 ,NumRead_14 ,NumRead_15 ,NumRead_17 ,NumRead_18 ,NumRead_19 ,NumRead_21 ,NumRead_22 ,NumRead_R_2 ,NumRead_R_4 ,NumRead_R_5 ,NumRead_R_10 ,NumRead_R_11 ,Add_S_02 ,Add_S_04 ,Add_S_06 ,Add_S_07 ,Add_S_11 ,Add_S_02_answ ,Add_S_08_answ ,Add_C_05 ,Sub_C_05_answ ,Pho_Elis_05 ,Banuca8_CM_7_resp ,

28==>[287, 292, 296, 304, 306, 308, 312, 313, 315, 327, 328, 330, 331, 333, 807]
Variable Names ==>
NumRead_R_28 ,Add_S_05 ,Add_S_09 ,Add_S_05_answ ,Add_S_07_answ ,Add_S_09_answ ,Add_C_01 ,Add_C_02 ,Add_C_04 ,Add_C_01_answ ,Add_C_02_answ ,Add_C_04_answ ,Add_C_05_answ ,Add_C_07_answ ,Banuca4_SS_7_resp ,

20==>[290, 295, 302, 342, 351, 372, 424, 426, 428, 430, 1188, 1189, 1190, 1191, 1192, 1193, 1194, 1195, 1196, 1197, 1198, 1199, 1200, 1201, 1202, 1203, 1204, 1205, 1206, 1207, 1208, 1209, 1210, 1211, 1212, 1213, 1214, 1215]
Variable Names ==> Add_S_03 ,Add_S_08 ,Add_S_03_answ ,Sub_S_01 ,Sub_S_10 ,Sub_C_07 ,Prob_01 ,Prob_03 ,Prob_05 ,Prob_07 ,Mul_S_01 ,Mul_S_02 ,Mul_S_03 ,Mul_S_04 ,Mul_S_05 ,Mul_S_06 ,Mul_S_07 ,Mul_S_08 ,Mul_S_09 ,Mul_S_10 ,Mul_S_11 ,Mul_S_12 ,Mul_S_13 ,Mul_S_14 ,Mul_S_15 ,Mul_C_01 ,Mul_C_02 ,Mul_C_03 ,Mul_C_04 ,Mul_C_05 ,Mul_C_06 ,Mul_C_07 ,Mul_C_08 ,Mul_C_09 ,Mul_C_10 ,Mul_C_11 ,Mul_C_12 ,Mul_C_13 ,

25==>[303, 311, 344, 345, 346, 354, 355, 357, 358, 425, 429, 433, 434, 436, 437, 438, 440, 441, 442, 446, 560, 668, 738]
Variable Names ==> Add_S_04_answ ,Add_S_12_answ ,Sub_S_03 ,Sub_S_04 ,Sub_S_05 ,Sub_S_01_answ ,Sub_S_02_answ ,Sub_S_04_answ ,Sub_S_05_answ ,Prob_02 ,Prob_06 ,Prob_10 ,Prob_11 ,Prob_R_1 ,Prob_R_2 ,Prob_R_3 ,Prob_R_5 ,Prob_R_6 ,Prob_R_7 ,Prob_R_11 ,Five_Dig_Read_E ,TDE_Read_46 ,Rey_rec1_10 ,

38==>[360, 381, 397, 411, 412, 413, 414, 415, 416, 417, 418, 420, 421, 422, 492, 556, 864, 869, 996]
Variable Names ==> Sub_S_07_answ ,Sub_C_01_answ ,Mul_S_02_answ ,Mul_C_01_answ ,Mul_C_02_answ ,Mul_C_03_answ ,Mul_C_04_answ ,Mul_C_05_answ ,Mul_C_06_answ ,Mul_C_07_answ ,Mul_C_08_answ ,Mul_C_10_answ ,Mul_C_11_answ ,Mul_C_12_answ ,OV_CB_np ,Pho_Elis_25 ,Banuca8_CM_4 ,Banuca8_CM_9 ,Consistencia_Lat_H ,

35==>[448, 449, 452, 454, 457, 458, 459, 460, 461, 467, 468, 471, 473, 476, 477,

478, 479, 480]
Variable Names ==> CB_bath ,CB_maid ,CB_dw ,CB_freezer ,CB_mcw ,CB_moto ,CB_drm ,CB_water ,CB_street ,CB_bath_score ,CB_maid_score ,CB_dw_score ,CB_freezer_score ,CB_mw_score ,CB_moto_score ,CB_drm_score ,CB_water_score ,CB_street_score ,

36==>[450, 451, 455, 456, 469, 470, 474, 475]
Variable Names ==>
CB_car ,CB_computador ,CB_wm ,CB_dvd ,CB_car_score ,CB_computer_score ,CB_wm_score ,CB_dvd_score

37==>[453, 462, 463, 466, 472, 481, 484, 486, 490, 495, 497, 501, 998, 999]
Variable Names ==> CB_fridge ,CB_Father_educ ,CB_Mother_educ ,CB_income ,CB_fridge_score ,CB_housedl_score ,OV_CB_bath ,OV_CB_hm ,OV_CB_freezer ,OV_CB_bath_score ,OV_CB_hm_score ,OV_CB_freezer_score ,SES_juntado ,SES_justado_non
,

34==>[464, 482, 483, 485, 487, 488, 493, 494, 496, 498, 499]

Variable Names ==>
CB_People_House ,OV_CB_tv ,OV_CB_radio ,OV_CB_car ,OV_CB_wm ,OV_CB_dvd ,OV_CB_tv_score ,OV_CB_radio_score ,OV_CB_car_score ,OV_CB_wm_score ,OV_CB_dvd_score ,

41==>[489, 500, 523, 809, 982, 983, 984, 997, 1542, 1548, 1552, 1554, 1555, 1556]
Variable Names ==> OV_CB_ref ,OV_CB_ref_score ,MAQ_MC_03 ,Banuca5_LN_1 ,FT_D_1 ,FT_D_2 ,FT_RH_mean_final ,Consistencia_Lat_HYF ,NM_Pantonima1 ,SequenciaMotora ,Oponencia ,Oseretski ,Impersistencia_motora ,NM_Tanden_tras ,

33==>[491, 502, 503, 504, 732, 897, 985, 988]

Variable Names ==>
OV_CB_iy ,OV_CB_iy_score ,OV_Mother_ed_level ,OV_Father_ed_level ,Rey_rec1_4 ,Banuca9_RA_2_resp ,NM_Fgnosia_RH_1 ,NM_Fgnosia_LH_1 ,

42==>[537, 541, 546, 548, 550, 551, 552, 553, 557, 559, 564, 761]
Variable Names ==> Pho_Elis_06 ,Pho_Elis_10 ,Pho_Elis_15 ,Pho_Elis_17 ,Pho_Elis_19 ,Pho_Elis_20 ,Pho_Elis_21 ,Pho_Elis_22 ,Pho_Elis_26 ,Pho_Elis_28 ,Pho_Elis_Percentage ,Rey_rec2_15 ,

24==>[584, 585, 586, 587, 588, 589, 590, 591, 592, 594, 595, 596, 597, 598, 600, 601, 602, 603, 604, 605, 606]

Variable Names ==>

Est_median_2 ,Est_median_3 ,Est_median_4 ,Est_median_5 ,Est_median_10 ,Est_median_16 ,Est_median_24 ,Est_median_32 ,Est_median_48 ,Est_median_64 ,Est_RT_mean_1 ,Est_RT_mean_2 ,Est_RT_mean_3 ,Est_RT_mean_4 ,Est_RT_mean_10 ,Est_RT_mean_16 ,Est_RT_mean_24 ,Est_RT_mean_32 ,Est_RT_mean_48 ,Est_RT_mean_56 ,Est_RT_mean_64 ,

9==>[894, 920, 922, 929, 930, 932, 933, 934, 937, 938, 939, 940, 941, 942]
Variable Names ==> Banuca9_RA_14 ,Num_Line_Paper_4 ,Num_Line_Paper_23 ,Num_Line_Paper_12 ,Num_Line_Paper_25 ,Num_Line_Paper_39 ,Num_Line_Paper_17 ,Num_Line_Paper_48 ,Num_Line_Paper_21 ,Num_Line_Paper_43 ,Num_Line_Paper_29 ,Num_Line_Paper_57 ,Num_Line_Paper_33 ,Num_Line_Paper_6 ,

15==>[992, 1066, 1531, 1532, 1533, 1534, 1535, 1536, 1537, 1538, 1539, 1540, 1541, 1543, 1544, 1545, 1546, 1547, 1549, 1550, 1551, 1553, 1557, 1558, 1559, 1560, 1561, 1562, 1563, 1564, 1565, 1566, 1567]
Variable Names ==>
NM_index_nose_eyes_open ,hand_preferencia ,NM_Lat_H_1 ,NM_Lat_H_2 ,NM_Lat_H_3 ,NM_Lat_H_result ,NM_Lat_Y_1 ,NM_Lat_Y_2 ,NM_Lat_Y_3 ,NM_Lat_Y_result ,NM_Lat_F_result ,NM_Moeda_D ,NM_Moeda_E ,NM_Pantonima2 ,NM_Pantonima3 ,NM_Pantonima4 ,NM_Pantonima5 ,NM_Pantonima6 ,InstrucesConflitantes ,GonoGo ,index_index ,Disdiadococinesia ,NM_Romberg ,NM_Reacao_eq_frente ,NM_Reacao_eq_tras ,NM_Reacao_eq_lat ,NM_Corrida ,NM_Marcha_ponta_pe ,NM_Marcha_calcanhar ,NM_Apoio_unipodal ,NM_Salto_palmas ,NM_Polichinelo ,NM_Coordenacao ,

29==>[1014, 1015, 1016, 1017, 1028, 1029, 1030, 1031, 1058, 1059, 1060, 1061]
Variable Names ==> Corsi_F_6_1 ,Corsi_F_6_2 ,Corsi_F_7_1 ,Corsi_F_7_2 ,Corsi_B_5_1 ,Corsi_B_5_2 ,Corsi_B_6_1 ,Corsi_B_6_2 ,Dspan_B_4_1 ,Dspan_B_4_2 ,Dspan_B_5_1 ,Dspan_B_5_2 ,

30==>[1018, 1019, 1032, 1033, 1034, 1035, 1046, 1047, 1048, 1049, 1050, 1051, 1062, 1063, 1064, 1065]
Variable Names ==> Corsi_F_8_1 ,Corsi_F_8_2 ,Corsi_B_7_1 ,Corsi_B_7_2 ,Corsi_B_8_1 ,Corsi_B_8_2 ,Dspan_F_6_1 ,Dspan_F_6_2 ,Dspan_F_7_1 ,Dspan_F_7_2 ,Dspan_F_8_1 ,Dspan_F_8_2 ,Dspan_B_6_1 ,Dspan_B_6_2 ,Dspan_B_7_1 ,Dspan_B_7_2 ,

11==>[1067, 1068, 1069, 1070, 1071, 1072, 1073, 1074, 1075, 1076, 1077, 1078, 1079, 1080, 1081, 1082, 1083, 1084, 1085, 1086, 1087, 1088, 1089, 1090, 1091, 1092, 1093, 1094, 1095, 1096, 1097, 1098, 1099, 1100, 1101, 1102, 1103, 1104, 1105, 1106]
Variable Names ==> Transc_1 ,Transc_2 ,Transc_3 ,Transc_4 ,Transc_5 ,Transc_6 ,Transc_7 ,Transc_8 ,Transc_9 ,Transc_10 ,Transc_11 ,Transc_12 ,Transc_13 ,Transc_14 ,Transc_15 ,Transc_16 ,Transc_17 ,Transc_18 ,Transc_19 ,Transc_20 ,Transc_21 ,Transc_22 ,Transc_23 ,Transc_24 ,Transc_25 ,Transc_26 ,Transc_27 ,Transc_28 ,Transc_29 ,Transc_30

,Transc_31 ,Transc_32 ,Transc_33 ,Transc_34 ,Transc_35 ,Transc_36 ,Transc_37 ,Transc_38 ,Transc_39 ,Transc_40 ,

21==>[1244, 1245, 1248, 1249, 1251, 1256, 1257, 1261, 1262, 1263, 1264, 1267, 1269, 1277, 1278, 1280, 1282, 1284, 1286, 1305, 1309, 1310, 1316, 1322, 1326, 1334, 1338, 1341, 1342, 1343, 1352]
Variable Names ==> CBCL_3 ,CBCL_4 ,CBCL_7 ,CBCL_8 ,CBCL_10 ,CBCL_15 ,CBCL_16 ,CBCL_20 ,CBCL_21 ,CBCL_22 ,CBCL_23 ,CBCL_26 ,CBCL_28 ,CBCL_36 ,CBCL_37 ,CBCL_39 ,CBCL_41 ,CBCL_43 ,CBCL_45 ,CBCL_57 ,CBCL_61 ,CBCL_62 ,CBCL_68 ,CBCL_74 ,CBCL_78 ,CBCL_86 ,CBCL_90 ,CBCL_93 ,CBCL_94 ,CBCL_95 ,CBCL_104 ,

1==>[1362, 1413, 1415, 1416, 1417, 1418, 1419, 1420, 1421, 1422, 1423, 1424, 1425, 1426, 1428, 1429, 1430, 1431, 1432, 1433, 1434]
Variable Names ==> TDE_Spell_name ,TDE_Arit_14 ,TDE_Arit_16 ,TDE_Arit_17 ,TDE_Arit_18 ,TDE_Arit_19 ,TDE_Arit_20 ,TDE_Arit_21 ,TDE_Arit_22 ,TDE_Arit_23 ,TDE_Arit_24 ,TDE_Arit_25 ,TDE_Arit_26 ,TDE_Arit_27 ,TDE_Arit_29 ,TDE_Arit_30 ,TDE_Arit_31 ,TDE_Arit_32 ,TDE_Arit_33 ,TDE_Arit_34 ,TDE_Arit_35 ,

2==>[1363, 1364, 1365, 1366, 1367, 1368, 1369, 1370, 1371, 1372, 1373, 1374, 1375, 1376, 1377, 1378, 1379, 1380, 1381, 1382, 1383, 1384, 1385, 1386, 1387, 1388, 1389, 1390, 1391, 1392, 1393, 1394, 1395, 1396, 1397, 1398, 1399, 1400, 1401, 1402, 1403, 1404, 1405, 1406, 1407, 1408, 1409, 1410, 1411, 1412, 1414, 1427]

Variable Names ==>
TDE_Spell_1 ,TDE_Spell_2 ,TDE_Spell_3 ,TDE_Spell_4 ,TDE_Spell_5 ,TDE_Spell_6 ,TDE_Spell_7 ,TDE_Spell_8 ,TDE_Spell_9 ,TDE_Spell_10 ,TDE_Spell_11 ,TDE_Spell_12 ,TDE_Spell_13 ,TDE_Spell_14 ,TDE_Spell_15 ,TDE_Spell_16 ,TDE_Spell_17 ,TDE_Spell_18 ,TDE_Spell_19 ,TDE_Spell_20 ,TDE_Spell_21 ,TDE_Spell_22 ,TDE_Spell_23 ,TDE_Spell_24 ,TDE_Spell_25 ,TDE_Spell_26 ,TDE_Spell_27 ,TDE_Spell_28 ,TDE_Spell_29 ,TDE_Spell_30 ,TDE_Spell_31 ,TDE_Spell_32 ,TDE_Spell_33 ,TDE_Spell_34 ,TDE_Arit_oral_1 ,TDE_Arit_oral_2 ,TDE_Arit_oral_3 ,TDE_Arit_1 ,TDE_Arit_2 ,TDE_Arit_3 ,TDE_Arit_4 ,TDE_Arit_5 ,TDE_Arit_6 ,TDE_Arit_7 ,TDE_Arit_8 ,TDE_Arit_9 ,TDE_Arit_10 ,TDE_Arit_11 ,TDE_Arit_12 ,TDE_Arit_13 ,TDE_Arit_15 ,TDE_Arit_28 ,

18==>[1435, 1436, 1437, 1438, 1439, 1440, 1441, 1442, 1443, 1444, 1445, 1446, 1447, 1448, 1449, 1450, 1451, 1452, 1453, 1454, 1455, 1456, 1457, 1458, 1459, 1460, 1461, 1462, 1463, 1464, 1465, 1466, 1467, 1468, 1469, 1470, 1471, 1472, 1473, 1474, 1475, 1476, 1477, 1478, 1479, 1480, 1481, 1482, 1483, 1484, 1485, 1486, 1487, 1488, 1489, 1490, 1491, 1492, 1493, 1494]

Variable Names ==>
LPI_Reg_01 ,LPI_Reg_02 ,LPI_Reg_03 ,LPI_Reg_04 ,LPI_Reg_05 ,LPI_Reg_06 ,LPI_Reg_07 ,LPI_Reg_08 ,LPI_Reg_09 ,LPI_Reg_10 ,LPI_Reg_11 ,LPI_Reg_12 ,LPI_Reg_13 ,LPI_Reg_14 ,LPI_Reg_15 ,LPI_Reg_16 ,LPI_Reg_17 ,LPI_Reg_18 ,LPI_Reg_19 ,LPI_Reg_20 ,LPI_Irreg_01 ,LPI_Irreg_02 ,LPI_Irreg_03 ,LPI_Irreg_04 ,LPI_Irreg_05 ,LPI_Irreg_06 ,LPI_Irreg_07 ,LPI_Irreg_08 ,LPI_Irreg_09 ,LPI_Irreg_10 ,LPI_Irreg_11 ,LPI_Irreg_12 ,LPI_Irreg_13 ,LPI_Irreg_14 ,LPI_Irreg_15 ,LPI_Irreg_16 ,LPI_Irreg_17 ,LPI_Irreg_18 ,LPI_Irreg_19 ,LPI_Irreg_20 ,LPI_Pseud_01 ,LPI_Pseud_02 ,LPI_Pseud_03 ,LPI_Pseud_04 ,LPI_Pseud_05 ,LPI_Pseud_06 ,LPI_Pseud_07 ,LPI_Pseud_08 ,LPI_Pseud_09 ,LPI_Pseud_10 ,LPI_Pseud_11 ,LPI_Pseud_12 ,LPI_Pseud_13 ,LPI_Pseud_14 ,LPI_Pseud_15 ,LPI_Pseud_16 ,LPI_Pseud_17 ,LPI_Pseud_18 ,LPI_Pseud_19 ,LPI_Pseud_20

23==>[1495, 1496, 1497, 1498, 1499, 1500, 1501, 1502, 1503, 1504, 1505, 1506, 1507, 1508, 1509, 1510, 1511, 1512, 1513, 1514, 1515, 1516, 1517, 1518, 1519, 1520, 1521, 1522, 1523, 1524, 1525, 1526, 1527, 1528, 1529, 1530]
Variable Names ==>
Raven_A_1 ,Raven_A_2 ,Raven_A_3 ,Raven_A_4 ,Raven_A_5 ,Raven_A_6 ,Raven_A_7 ,Raven_A_8 ,Raven_A_9 ,Raven_A_10 ,Raven_A_11 ,Raven_A_12 ,Raven_AB_1 ,Raven_AB_2 ,Raven_AB_3 ,Raven_AB_4 ,Raven_AB_5 ,Raven_AB_6 ,Raven_AB_7 ,Raven_AB_8 ,Raven_AB_9 ,Raven_AB_10 ,Raven_AB_11 ,Raven_AB_12 ,Raven_B_1 ,Raven_B_2 ,Raven_B_3 ,Raven_B_4 ,Raven_B_5 ,Raven_B_6 ,Raven_B_7 ,Raven_B_8 ,Raven_B_9 ,Raven_B_10 ,Raven_B_11 ,Raven_B_12