

Universidad de Alcalá

Escuela Politécnica Superior

Grado en Ingeniería Informática

Trabajo Fin de Grado

On the Data Quality Characteristics of Software Engineering
Defect Prediction Datasets

Autor: Pablo Acereda García

Tutor: Daniel Rodríguez García

2020

UNIVERSIDAD DE ALCALÁ
ESCUELA POLITÉCNICA SUPERIOR

Grado en Ingeniería Informática

Trabajo Fin de Grado

**On the Data Quality Characteristics of Software Engineering
Defect Prediction Datasets**

Autor: Pablo Acereda García

Director: Daniel Rodríguez García

Tribunal:

Presidente:

Vocal 1º:

Vocal 2º:

Calificación:

Fecha:

A quien le haga falta saberlo...

“Si tienes un problema que no tiene solución, ¿para qué te preocupas? Y si tiene solución, ¿para qué te preocupas?”

Proverbio chino, y de mi abuela

Acknowledgements

Sin entrenamiento, no existe el conocimiento. Sin conocimiento, no existe la confianza. Sin confianza, la victoria no existe.

Julio César

Tras muchas horas de esfuerzo, querer tirarme de los pelos, dar cabezazos contra la pared o querer gritar... simplemente han pasado 4 años, sin darme cuenta. Siempre he tenido junto a mí el apoyo de mi familia o amigos; también he conocido a quienes los considero como a mis hermanos; hay quienes han venido, han dejado su marca, y han venido casi sin despedirse - pero todo ello me ha hecho convencerme de un solo dogma: no podría haber hecho esto solo.

De mi familia, especialmente mis padres y hermana siempre he sacado el apoyo moral que consigue levantar montañas. Me han dado la oportunidad de ser yo el que vaya cometiendo mis propios errores y aprendiendo de ellos; pero sobre todo - conocerme a mí mismo. Gracias por dar vuestro mejor esfuerzo para que yo haya podido llegar hasta aquí, por haberme educado para ser siempre curioso y no conformarme con nada, por haberme regañado cuando he errado y animado cuando lo he conseguido. Otra pequeña mención para mis abuelos, por haberme enseñado cosas sobre la vida, sobre cosas que no están escritas en los libros, pero son igual o más importantes.

A mi pareja, por hacerme descansar después de inacabables jornadas de trabajo, por aquellas largas noches hablando sobre la vida y riéndonos de nosotros mismos hasta casi llorar de la risa. Gracias por hacerme ver el mundo y ser mi hogar. Agradezco a mis amigos de toda la vida por hacerme darme cuenta de que las cosas no siempre son tan malas como parecen, que a veces pararme y coger aire te hace seguir adelante.

Gracias a mi *hermanita* por enseñarme que sin importar lo difícil que sea la vida, siempre se puede seguir adelante con la cabeza alta y una sonrisa en la cara que anime a quien sea. Me mantuviste despierto allí donde la noche se hacía larga, pero los quehaceres no desaparecían.

No me olvido del griego que me enseñó a cuidarme y que, en muchas ocasiones, hizo de hermano mayor. Jamás olvidaré que fuiste tú el que me enseñó que la palabra abre muchas puertas, y que si quieres cambiar el mundo primero tienes que cambiarte a ti mismo.

Por esas risas y barbacoas en las que se aprenden lecciones de vida importaditas por *Overflow*. Me hacéis querer seguir superándome cada día.

No olvido las cenas pendientes con los *lobos* en las que solo se escucha gritar “*Que no soy el lobo!*” pero que nos da años de vida.

Gracias al ciclista y a la profesora de mi tierra por traerme a esta universidad que me ha enseñado tanto y de la que me llevo increíbles recuerdos.

Por último, pero no por ello menos importante, agradezco a mi tutor todas las horas y esfuerzo invertidos en este proyecto a pesar de que las circunstancias no nos acompañaban. Espero que todo mejore con el tiempo. Muchas gracias por tu apoyo.

Mirando atrás, tengo muchas cosas que me llevo y que guardaré en mi memoria hasta que esta empiece a fallar.

Resumen

En el área de desarrollo de código, el *Machine Learning* puede ayudar de varias maneras, como por ejemplo en la detección de código defectuoso. Existen diferentes estudios que tienen como objetivo el identificar dichos módulos defectuosos, aunque en este trabajo, nos centramos en los problemas relacionados con sets de datos creados a partir de dichos módulos, su complejidad y desbalanceo. En el campo de la minería de datos, los clasificadores tratan de optimizar su rendimiento centrándose sobre la clase mayoritaria. Esto implica que un clasificador no dará los resultados esperados en conjuntos de datos desbalanceados, donde las muestras de la clase minoritaria son insignificantes en comparación con las muestras de la clase mayoritaria; o cuando dichas muestras se solapan. Este proyecto intenta analizar las métricas anteriormente mencionadas para ver como estas afectan al rendimiento del clasificador.

Palabras clave: Data Mining, Desbalanceo, Métricas de Complejidad, Under Sampling, Over Sampling.

Abstract

When developing code, machine learning techniques can help in a variety of ways, one of them is predicting defective modules. There are many works trying to identify defective modules but in this work we focus on one of the problems related to the datasets used to induce such modules, its complexity, including imbalance. Data mining classifiers tend to optimize the performance by focusing on the majority class first. That means that they perform poorly when dealing with imbalanced datasets, where the minority class is outnumbered by the number of samples of the majority class; or when samples overlap. In real world problems, this kind of distribution is common. This project tries to analyze those metrics to see what complexity metrics affect the classification performance.

Keywords: Data Mining, Imbalanced Data, Complexity Metrics, Under Sampling, Over Sampling.

Contents

Resumen	IX
Abstract	XI
Contents	XIII
List of Figures	XVII
List of Tables	XIX
List of Acronyms	XIX
List of Symbols	XIX
1. Introduction	1
1.1. Introduction to Machine Learning	1
1.2. Aim and Objectives	1
2. Background	3
2.1. Data Complexity Metrics	3
2.1.1. Measures of Overlap of Individual Feature Values	4
2.1.1.1. Fisher's Discriminant Ratio (F1)	4
2.1.1.2. Directional Vector Fishers Discriminant Ratio (F1v)	4
2.1.1.3. Volume of Overlap Region (F2)	4
2.1.1.4. Feature Efficiency (F3)	4
2.1.1.5. Collective Feature Efficiency (F4)	5
2.1.2. Measures of Neighborhood	5
2.1.2.1. Mixture Identifiability (N1, N2, N3)	5
2.1.2.2. Non-linearity of the Nearest Neighbor Classifier (N4)	5
2.1.2.3. Fraction of Hyper-spheres Covering Data (T1)	5
2.1.2.4. Local Set Average Cardinality (LSC)	5
2.1.3. Measures of Separability of Classes	5

2.1.3.1.	Linear Separability (L1, L2, L3)	6
2.1.4.	Measures of Dimensionality	6
2.1.4.1.	Average Number of samples per dimension (T2)	6
2.1.4.2.	Average intrinsic dimensionality per number of samples (T3)	6
2.1.4.3.	Intrinsic dimensionality proportion (T4)	6
2.1.5.	Measures of Class Balance	6
2.1.5.1.	Entropy of class proportions (C1)	6
2.1.5.2.	Multi-class imbalance ratio (C2)	7
2.1.6.	Measures of Network	7
2.1.6.1.	Average density of of network (Density)	7
2.1.6.2.	Clustering Coefficient (ClsCoef)	7
2.1.6.3.	Average hub score (Hubs)	7
2.1.7.	Measures of Feature Correlation	7
2.1.7.1.	Maximum/Average feature correlation to the output (C1, C2)	7
2.1.7.2.	Individual feature efficiency (C3)	7
2.1.7.3.	Collective feature efficiency (C4)	7
2.1.8.	Measures of Smoothness	8
2.1.8.1.	Output distribution (S1)	8
2.1.8.2.	Input distribution (S2)	8
2.1.8.3.	Error of a nearest neighbor regressor (S3)	8
2.1.8.4.	Non-linearity of nearest neighbor regressor (S4)	8
2.2.	Supervised Methods	9
2.3.	Imbalance	9
2.3.1.	Sampling Techniques	10
2.3.1.1.	Undersampling	10
2.3.1.2.	Oversampling	11
2.3.2.	Cost-Sensitive Classifiers	12
2.3.3.	Ensembles	12
2.3.4.	Hybrid Approaches	13
2.3.5.	Defect Prediction	13
3.	Empirical Work	15
3.1.	Datasets	15
3.2.	Supervised Classifiers	17
3.3.	Evaluation Metrics	18
3.3.1.	Precision	19
3.3.2.	Recall	19

3.3.3. Fall-out	19
3.3.4. Balance Accuracy	19
3.3.5. F-Measure	20
3.3.6. MCC	20
3.3.7. Receiver Operating Characteristic Curve	20
3.4. Results and discussion	21
3.4.1. Methodology	21
3.4.2. Data Complexity Metrics Analysis	21
3.4.3. Cross Validation Analysis	24
3.4.4. Imbalance Experimental Work	26
3.4.4.1. Undersampling with Cross Validation	26
3.4.4.2. Oversampling with Cross Validation	28
3.4.5. Comparison of the Results and Discussion	30
4. Conclusions and Future Work	35
4.1. Conclusions	35
4.2. Future Work	36
Bibliography	37
A. Prerequisites	41
B. Python Relevant Code	43
B.1. Rserve Python Client	43
B.2. Datasets and Operations on Data	45
B.3. Experiment 1. Complexity Metrics Comparison	52
B.4. Experiment 2. Compare Metrics on K-fold Cross Validation	55
B.5. Experiment 3. Compare Metrics with Under-sampling and K-fold Cross Validation	57
B.6. Experiment 4. Compare Metrics with Over-sampling and K-fold Cross Validation	59
C. Tables	61
C.1. Complexity Metrics OO datasets	61
C.2. Complexity Metrics Hadoop datasets	62
D. Figures	63
D.1. Complexity Metrics	63

List of Figures

2.1. Undersampling Technique [1]	10
2.2. Oversampling Technique [1]	11
3.1. ROC Curve	20
3.2. Balance Measures	22
3.3. Correlation Measures	22
3.4. Dimensionality Measures	22
3.5. Linearity Measures	22
3.6. Neighborhood Measures	23
3.7. Network Measures	23
3.8. Overlap Measures	23
3.9. Smoothness Measures	24
D.1. Overlap F1	63
D.2. Overlap F1v	63
D.3. Overlap F2	63
D.4. Overlap F3	64
D.5. Overlap F4	64
D.6. Neighborhood N1	64
D.7. Neighborhood N2	64
D.8. Neighborhood N3	64
D.9. Neighborhood N4	65
D.10. Neighborhood T1	65
D.11. Neighborhood LSC	65
D.12. Linearity L1	65
D.13. Linearity L2	65
D.14. Linearity L3	66
D.15. Dimensionality T2	66
D.16. Dimensionality T3	66

D.17.Balance C1	66
D.18.Balance C2	66
D.19.Network Density	67
D.20.Network ClsCoef	67
D.21.Network Hubs	67
D.22.Correlation C2	67
D.23.Correlation C3	67
D.24.Correlation C4	68
D.25.Smoothness S1	68
D.26.Smoothness S2	68
D.27.Smoothness S3	68
D.28.Smoothness S4	68

List of Tables

2.1. Complexity Metrics from [2, 3]	8
3.1. Defect Metrics Dataset Variables	15
3.2. Description of the Datasets	16
3.3. Confusion Matrix for Binary Classification	19
3.4. Cross-Validation Results — Apache Dataset	25
3.5. Cross-Validation Results — Hadoop 0.8 Dataset	26
3.6. Cross-validation with Undersampling Results — Apache dataset	27
3.7. Cross-validation with Undersampling Results — Hadoop 0.8	28
3.8. Oversampling with Cross Validation Results — Apache dataset	29
3.9. Oversampling with Cross-Validation Results — Hadoop 0.8 dataset	30
3.10. All Metrics	32
3.11. All Metrics	33
3.12. All Metrics	34
C.1. Complexity Metrics Analysis	61
C.2. Complexity Metrics Analysis on Hadoop datasets	62

Chapter 1

Introduction

1.1. Introduction to Machine Learning

Through time, humans wanted to keep all memories or thoughts precious to them for posterity. Thanks to some technological advancements, large amounts of information can be stored for a relatively cheap price - videos, photographs, drawings, weather measures, financial information, academic data, etc. It can all be digitalized and kept *forever*. These new possibilities also brought new challenges. *What to do with all that information?* Data scientists try to manage and make some sense out of the overwhelming new information that is being continuously created.

The figure of a data scientist is the one who uses scientific methods, processes, algorithms and systems to extract knowledge from structured and unstructured data. The algorithms used in data science, are sequences of statistical processing steps. Then, there is Machine Learning which uses computer algorithms that improve through experience - it is also a subset of Artificial Intelligence (AI). In this case, the algorithms are *trained* to filter and discover patterns and features with massive amounts of data.

The training and learning processes allow us to make predictions and decisions for new data, being advantageous for almost any field: commercial purposes, fraud detection, fault prediction, health, environment (climate), network traffic, and so on.

The number of machine learning tools/techniques applied in this project is quite large and those are further explained in the *Background* (Section 2). As a brief introduction to the techniques and material in this paper, it has been used ECOL R package to obtain the complexity metrics of several datasets; the Python's `scikit-learn` package for learning algorithms and some performance metrics for the classification algorithms (used through the experiments); as well as the `imbalanced-learn` Python package to deal with imbalanced datasets. The resulting scripts allow us the visualization between different tables and plots for comparing results.

1.2. Aim and Objectives

Here we analyse the complexity metrics proposed by Ho and Basu [4] in a number of software defect datasets, that have been previously implemented in ECOL R package.

The aim of this work is to explore complexity metrics on software defect datasets. Also, to analyse how classification algorithms are affected by techniques that mitigate imbalance and how that affects the complexity metrics previously analysed. To do so, we explore several objectives:

- RQ1 How complexity metrics are correlated to the outcome of supervised algorithms?
- RQ2 How complexity metrics and imbalance are related?
- RQ3 Do complexity metrics tell us something about the quality of the datasets?

The purpose of this dissertation is to conduct a study of complexity metrics and imbalanced datasets. A comparison between the *raw* data and that data after performing some changes that should affect the results: *K*-folding Cross Validation (CV), imbalanced techniques, etc.

Chapter 2

Background

2.1. Data Complexity Metrics

There are many complexity metrics that could be used for the scope of this project, but it has been chosen the ones that are explained below; following the metrics obtained from [\[4\]](#), and surveys by Lorena et al [\[2,5\]](#) (see also [\[6\]](#)). They are also implemented in the Extended Complexity Metrics Library (ECoL) for R.

These are a set of measures that help characterizing the complexity of classification and regression problems. The measures that are going to be computed for this project are:

Overlapping Evaluate how informative the available features are to separate the classes. See [2.1.1](#) for more details.

Neighborhood Characterize the presence and density of classes in local neighborhoods. See [2.1.2](#) for more details.

Linearity Quantify, if it is possible, whether classes are linear separable by a hyperplane or linear function. See [2.1.3](#) for more details.

Dimensionality Indicative of data sparsity, how smoothly samples are distributed within attributes. See [2.1.4](#) for more details.

Balance Capture the difference in the number of examples per class in the dataset. See [2.1.5](#) for more details.

Network Represents the dataset as a graph and extracts structural information out of it. See [2.1.6](#) for more details.

Correlation Relationship between the feature values and the outputs. See [2.1.7](#) for more details.

Smoothness In regression problems, the smoother the function to be fitted to the data, the simpler it shall be. See [2.1.8](#) for more details.

These complexity measures are going to be computed for certain datasets and comparisons between results are going to be made.

2.1.1.1. Measures of Overlap of Individual Feature Values

An overlapped dataset is defined as a multi-class dataset where the data is interlaced. The meaning of this statement is explained as follows: having a dataset whose geometrical expression have the domain, D_n^1 , a second class will have a domain, D'_n , intersecting that of the first class.

2.1.1.1.1. Fisher's Discriminant Ratio (F1)

This metric is specific to one feature dimension. Even if the given problem is multidimensional, not necessarily all features have to contribute to class discrimination, only one of the features needs to be the discriminant. Fulfilling this statement would ease the complexity of the problem.

The measure uses the following mathematical expression:

$$f = \frac{(\mu_1 - \mu_2)^2}{\sigma_1^2 + \sigma_2^2}$$

Where $\mu_1, \mu_2, \sigma_1^2, \sigma_2^2$ are the means and variances, respectively, of the two classes².

2.1.1.1.2. Directional Vector Fishers Discriminant Ratio (F1v)

Complemented F1 (see Section 2.1.1.1). It does so by searching for a vector capable of separating two classes after the training samples have been projected into it.

2.1.1.1.3. Volume of Overlap Region (F2)

Another way to measure the complexity is by using the tails of the overlap of the classes. This is accomplished by taking the maximum and minimum values of each class. Afterwards, the length of overlap is calculated, normalized by range of the classes. This is done by:

$$f = \prod_i \frac{MIN(max(f_i, c_1), max(f_i, c_2)) - MAX(min(f_i, c_1), min(f_i, c_2))}{MAX(max(f_i, c_1), max(f_i, c_2)) - MIN(min(f_i, c_1), min(f_i, c_2))}$$

Where f_i indicates the feature; c_n indicates the class; and i indicates the dimensionality of the problem.

2.1.1.1.4. Feature Efficiency (F3)

In this measure, in high-dimensional problems, each feature is evaluated separately on how much it contributes to the separation of the classes. If there exists overlap within the range of each class for a certain feature, the class is considered to be ambiguous for that dimension in the specific region where the overlap takes place.

Therefore a problem will be more feasible if there exists at least one feature where the ranges for each class do not overlap. Thus, the *maximum feature efficiency* will be used as a measure. This measure is obtained with the entire training set, by obtaining the remaining points being separable by the feature.

¹Being n the number of attributes for that class

²It has been used two classes for the definition of the metric, but more classes could be added to the problem.

2.1.1.5. Collective Feature Efficiency (F4)

It gives an overview on how different features may work together in data separation. The most discriminant feature (see F3 - 2.1.1.4) is selected and then all samples separable by this feature are removed from the dataset. This process is repeated with all the features until no samples are left. The resulting value of this metric comes from the ratio of samples that have been discriminated.

2.1.2. Measures of Neighborhood

For a certain set of target classes in a dataset, the neighborhood measures try to analyze the neighbor data items of every data point and try to capture class overlapping and the shape of the decision boundary. The work is done over a distance matrix which stores distances between all pairs of data points in the dataset.

2.1.2.1. Mixture Identifiability (N1, N2, N3)

The measure is defined as the mean Euclidean distance from each point in the dataset, to its nearest neighbors, not minding the class they are in [7]. The valuable rates that can be taken are the means for interclass neighbors and intraclass neighbors.

2.1.2.2. Non-linearity of the Nearest Neighbor Classifier (N4)

It builds a new dataset by interpolating pairs of training samples of the same class and the induce a 1NN classifier on the original data and measure the error rate in the new data points.

2.1.2.3. Fraction of Hyper-spheres Covering Data (T1)

It creates a hyper-sphere centered at each one of the training samples. Their radios are then growth until one hyper-sphere reaches a sample of other class. Then, smaller hyper-spheres contained in larger hyper-spheres are eliminated. This measure is the ratio between the number of remaining hyper-spheres and the total number of samples in the dataset.

2.1.2.4. Local Set Average Cardinality (LSC)

It is a set of points from the dataset whose distance of each sample is smaller than the distance from the samples of the different classes.

2.1.3. Measures of Separability of Classes

Given two, or more classes, inside a certain dataset, they can be called linear separable if a straight line between those classes can be drawn. As the previous statement suggests, the classes must be isolated clusters after the linear function is delimited.

2.1.3.1. Linear Separability (L1, L2, L3)

As a way to adapt to separable and non-separable problems, it is used the formulation proposed by Smith [8], which minimizes an error function:

$$\begin{aligned} & \text{minimize } a^t t \\ & \text{subject to } Z^t w + t \geq b \\ & \quad t \geq 0 \end{aligned}$$

Implying that a and b are vectors; w is the weight vector; t is the error vector and Z is a matrix obtained by adding one dimension, with value one, to the input vector x .

2.1.4. Measures of Dimensionality

For any dataset, the dimensionality measures will indicate data sparsity. These measures capture how sparse a dataset tends to have regions of low density. These regions have been proven to be harder for the extraction of good classification and regression models.

2.1.4.1. Average Number of samples per dimension (T2)

It represents the average number of points per dimension. It is calculated with the ratio between the number of examples and dimensionality of the dataset.

2.1.4.2. Average intrinsic dimensionality per number of samples (T3)

Another way to measure the dimensionality of a dataset, is by computing the average of number of points per PCA. It is a similar measure to $T2$, which uses the number of PCA components needed to represent 95 variability as the base of a data sparsity assessment.

2.1.4.3. Intrinsic dimensionality proportion (T4)

It represents a ratio of PCA Dimensions to the original. It returns an estimate of the proportion of relevant and original dimensions of the dataset.

2.1.5. Measures of Class Balance

Given a dataset, *balance measures* capture the differences in the number of samples per class for that dataset. When the imbalance ratio is too severe, problems related to generalization of classification techniques can happen.

2.1.5.1. Entropy of class proportions (C1)

This measure captures the imbalance of a dataset using proportions of samples per class.

2.1.5.2. Multi-class imbalance ratio (C2)

The ratio at hand represents an index calculated to measure a class balance. It is not only suited for binary class classification problems, but also is suited for multi-class classification problems.

2.1.6. Measures of Network

These measures create a graph representation of the dataset to extract structural information from it. The transformation between raw data and the graph representation is based on the epsilon-NN ($\epsilon - NN$) algorithm. Afterwards, a post-processing step is applied to the graph, pruning edges between samples of opposite classes.

2.1.6.1. Average density of of network (Density)

It is a representation of the count of edges in the graph, divided by the maximum number of edges between pairs of data points.

2.1.6.2. Clustering Coefficient (ClsCoef)

Computes the average of the clustering tendency of the vertices by the ratio of existent edges between neighbors and the total number of edges that could possibly exist between them.

2.1.6.3. Average hub score (Hubs)

Is given by the number of connections to other nodes, weighted by the amount of connections the neighbors have.

2.1.7. Measures of Feature Correlation

A regression task that calculate the correlation of the values of the features to the outputs. In case one feature is highly correlated to the output, it is understandable that simpler functions can be fitted to the data.

2.1.7.1. Maximum/Average feature correlation to the output (C1, C2)

Representation of the maximum/average value of the Spearman correlations for each feature and the output.

2.1.7.2. Individual feature efficiency (C3)

Returns the number of samples to be removed from the dataset to reach a high Spearman correlation value to the output.

2.1.7.3. Collective feature efficiency (C4)

Gives the ratio of samples removed from the dataset based on an iterative process of linear fitting between the features and the target attribute.

2.1.8. Measures of Smoothness

It is a regression task, used for regression problems. In those problems, the smoother the function to be fitted, the simpler the task it becomes. Large variations in input/output are an indication of the existence of more intricate relationships between them.

2.1.8.1. Output distribution (S1)

Checks if the samples joined in then MST have similar output values. The lower the value, the simpler the problem - where outputs of similar samples in the input space are also next to each other.

2.1.8.2. Input distribution (S2)

Monitors the similarity in the input space of data items with similar outputs based on distance.

2.1.8.3. Error of a nearest neighbor regressor (S3)

Stands for the mean squared error of a 1-nearest neighbor regressor using leave-one-out.

2.1.8.4. Non-linearity of nearest neighbor regressor (S4)

Computes the mean squared error of a 1-NN regressor to the new randomly interpolated points.

Table 2.1: Complexity Metrics from [2, 3]

Category	Name	Acronym	Min	Max	Asymptotic Cost
Feature-based	Maximum Fisher's discriminant ratio	F1	≈ 0	1	$O(m \cdot n)$
	Directional vector maximum Fisher's discriminant ratio	F1v	≈ 0	1	$O(m \cdot n \cdot n_c + m^3 \cdot n_c^2)$
	Volume of overlapping region	F2	0	1	$O(m \cdot n \cdot n_c)$
	Maximum individual feature efficiency	F3	0	1	$O(m \cdot n \cdot n_c)$
	Collective feature efficiency	F4	0	1	$O(m^2 \cdot n \cdot n_c)$
Neighborhood	Faction of borderline points	N1	0	1	$O(m \cdot n^2)$
	Ratio of intra/extra class NN distance	N2	0	≈ 1	$O(m \cdot n^2)$
	Error rate of NN classifier	N3	0	1	$O(m \cdot n^2)$
	Non linearity of NN classifier	N4	0	1	$O(m \cdot n^2 + m \cdot l \cdot n)$
	Fraction of hyper-spheres covering data	T1	0	1	$O(m \cdot n^2)$
	Local set average cardinality	LSC	0	$1 - \frac{1}{n}$	$O(m \cdot n^2)$
Linearity	Sum of the error distance by linear programming	L1	0	≈ 1	$O(n^2)$
	Error rate of linear classifier	L2	0	1	$O(n^2)$
	Non linearity of linear classifier	L3	0	1	$O(n^2 + m \cdot n \cdot n_c)$
Dimensionality	Average number of features per dimension	T2	≈ 0	m	$O(m + n)$
	Average number of PCA dimensions per points	T3	≈ 0	m	$O(m^2 \cdot n + m^3)$
	Ratio of the PCA dimension to the original dimension	T4	0	1	$O(m^2 \cdot n + m^3)$
Class Imbalance	Entropy of classes proportions	C1	0	1	$O(n)$
	Imbalance ratio	C2	0	1	$O(n)$
Network	Density	Density	0	1	$O(m \cdot n^2)$
	Clustering Coefficient	ClsCoef	0	1	$O(m \cdot n^2)$
	Hubs	Hubs	0	1	$O(m \cdot n^2)$
Correlation	Maximum Feature Correlation to the Output	C1	0	1	$O(n \cdot m \cdot \log m)$
	Average Feature Correlation to the Output	C2	0	1	$O(n \cdot m \cdot \log m)$
	Individual Feature Efficiency	C3	0	1	$O(n \cdot m^2)$
	Collective Feature Efficiency	C4	0	1	$O(n \cdot (d + n \cdot \log n))$
Smoothness	Output Distribution	S1	0	-	$O(n^2)$
	Input Distribution	S2	0	-	$O(m \cdot (n + \log m))$
	Error of a nearest neighbor regressor	S3	0	-	$O(n^2)$

2.2. Supervised Methods

There are mainly two machine Learning has different methods or styles available:

Supervised classification trains a model using completely labeled dataset.

Unsupervised classification ingests unlabeled data to either create groups (clustering) or associate variables (e.g., association rules).

Semi-supervised Uses smaller labeled dataset to set up a guide and large amounts of unlabeled data for feature extraction

In this work, we focus only on the first one, supervised classification, i.e., a machine learning model is built on data that all instances have labeled information on how to determine and classify new incoming data.

In supervised learning, an optimal scenario is considered when the model is able to label correctly unseen data.

For this project, supervised learning is used more as a mean rather than as a final goal, in the sense that it aims at exploring how some data quality characteristics affect the performance of supervised classification rather than trying to improve the performance itself.

2.3. Imbalance

On any dataset obtained from a real world environment, there will be a class within the target outputs that will be more predominant than the rest of the classes. When the difference between the predominant class and the rest of the classes is not “remarkable” the dataset is called balanced. On the other hand, the classes are imbalanced if the number of samples from one class vastly outnumbers the number of samples from the rest of the classes, this is called imbalance problem. This means, that not enough data from the minority classes is available to train the algorithm.

Even though it might seem as a trivial matter, having an overwhelming amount of samples of just one of the classes means that usually algorithm will be biased towards the majority class, failing to classify properly the rest of the classes.

Most canonical classification algorithms (e.g. SVM, decision tree and neural networks) suffer from the *majority class bias* - they perform nicely on balanced datasets, but very few of them does under an imbalanced scenario. Since most of these learning processes are oriented to global accuracy, the resulting classifiers tend to have majority class bias. This is translated to an apparent good performance, that acts poorly on terms of accuracy in the minority class.

re-weighting through the learning process.

All the aforementioned metrics about datasets (and some recommended for imbalanced datasets) do not say how to mitigate its effects on classification algorithms. The different approaches to achieve this goal - deal with imbalanced data - are sampling techniques, cost-sensitive, ensemble approaches or hybrid approaches. They are going to be briefly described in the incoming sections.

2.3.1. Sampling Techniques

Techniques that are classified as *Sampling Techniques* are oversampling and undersampling (or up-sampling and downsmampling). These methods are based on the addition or removal of instances of a given training dataset. The process of replicating or creating instances from a minority class towards a more balanced distribution (number of samples of majority and minority class are more or less similar) is called Random OverSampling (ROS); whereas Random Under-Sampling (RUS) is the procedure of removing instances from the majority class to reduce the difference between the amount of samples of each class.

Rather than using this early proposals, there can be found more sophisticated approaches generating new artificial samples, rather than the replication of already existing instances. Some of these proposals are going to be explained in the following sections.

2.3.1.1. Undersampling

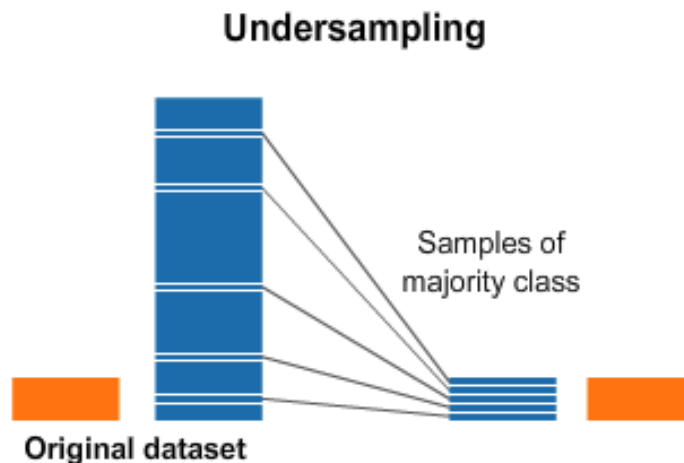


Figure 2.1: Undersampling Technique [1]

It involves removing samples from the dataset until the data is balanced. The reasons to use under-sampling are usually related to practical reasons, such as resource costs. The techniques presented are:

Undersampling involves deleting samples from the majority class, with or without replacement. It is one of the early proposals to deal with imbalanced datasets. Although it may alleviate the imbalance in the dataset, it may also increase the variance of the classifier or discard meaningful samples from the majority class.

Cluster Centroid replaces a cluster of samples by the cluster centroid of a *K-means* algorithm. The number of clusters is set by the level of undersampling.

Near Miss refers to a collection of undersampling methods that select samples based on the distance of the majority class samples to the minority class samples [9]. There are three versions of this algorithm:

1. *NearMiss-1* selects majority class samples with minimum average distance to three closest minority class samples;

2. *NearMiss-2* selects majority class examples with minimum average distance to the three furthest minority class examples;
3. *NearMiss-3* selects majority class examples with minimum distance to each minority class example.

Among all the available techniques, *Near Miss* has been the one used for this research. Other techniques that remove instances intelligently include the Edited Nearest Neighbor (ENN) and Wilson's Editing that remove instances in which close neighbors belong to a different class [10].

2.3.1.2. Oversampling

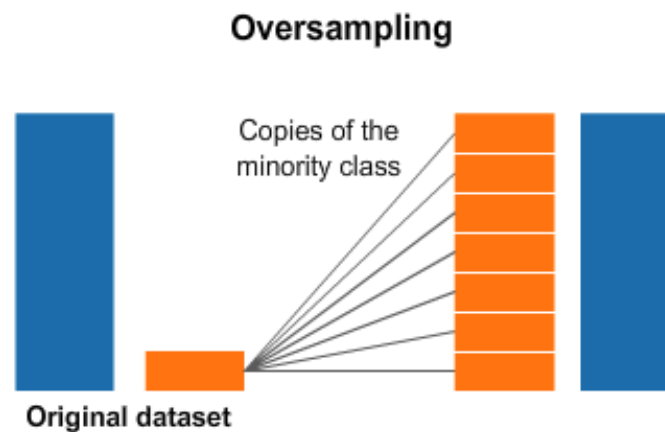


Figure 2.2: Oversampling Technique [1]

It involves replicating or creating new data points from the already existing data. The techniques analyzed are:

Oversampling involves copying supplementary data from the minority classes. It can be done more than once (actually, as many times as the developers sees fit). One of the early proposals regarding imbalanced datasets. It is robust, as it may randomly replace some of the samples from the minority class.

SMOTE (Synthetic Minority Oversampling Technique [11]) is one of the most popular oversampling techniques. It works by selecting samples close in the feature space. That means, that a line is drawn between the samples in the feature space and the a new sample at a point along that line. It is effective because the samples from the minority class created are plausible - relatively close in feature space to existing samples from minority class. A downside of this technique is that samples are created without looking at the majority class, meaning a possible overlapping of classes.

ADASYN (ADaptative SYNthetic) sampling algorithm was developed using the SMOTE approach shifting the importance of the classification boundary to those minority classes which are difficult. It weights the most difficult to learn classes so that those have more importance when creating new data. In other words, ADASYN generates more synthetic data in the minority class samples that are harder to learn.

The technique selected for this article is the SMOTE method, implemented by the *imbalanced-learn*³ Python package.

2.3.2. Cost-Sensitive Classifiers

Also known as CSC. These are adapted classifiers that handle imbalanced datasets by either:

1. Adding weights to instances⁴.
2. Resampling the training data according to the costs assigned to each class in a predefined cost matrix.
3. Or generating a model that minimizes the expected cost⁵. The idea behind this methodology is to penalize differently each type of error - in the specific case of binary classification, the false positives (FP) and false negatives (FN).

The problem with CSC is defining the cost matrix as there is no systematic approach to do so. However, it is common practice to set the cost to equalize the class distribution.

2.3.3. Ensembles

Also known as meta-learners are a combination of multiple models with the objective of obtaining better predictions. They are typically classified as *Bagging*, *Boosting* and *Stacking* - Stacked generalization.

Bagging [12] (also known as Bootstrap aggregating) is a ensemble technique that involves a base learner applied to multiple equal size datasets. These datasets are created from the original data using bootstrapping. Predictions are made on voting of the individual predictions.

An advantage of this technique is that it does not require to modify any aspect of the learning algorithm, taking advantage of the instability of the base classifier to create diversity among individual ensembles - so that individual members of the ensemble perform well in different regions of the data. However, if the output is robust to perturbation of the data (like is the case with nearest-neighbor -NN- classifiers) the performance drops and should not be used with those base classifiers.

Boosting techniques generate multiple models that complement each other. The final objective is to induce models that improve certain regions of the data, where previous induced models had low performance. This can be achieved by increasing the weights of instances that have been wrongly classified. That way, new learners focus on those regions.

Classification is based on a weighted voted among all members of the ensemble. One of the most popular boosting algorithms is AdaBoost.M1 [13] for classification. The set of training examples is assigned an equal weight at the beginning and the weight of instances can be increased or decreased depending on the classification of the learner. The next iterations focus on those instances with higher weights. AdaBoost.M1 can be applied to any base learner.

Models from ensembles are difficult to interpret (black-box behavior), comparing them to decision trees or rules providing explanation of their decision making process.

³<https://imbalanced-learn.readthedocs.io/en/stable/>

⁴Can only be used if the base classifier algorithm allows it

⁵It can be obtained by multiplying the predicted probability distribution with the misclassification costs

2.3.4. Hybrid Approaches

There are other hybrid approaches that can be used. Like that ones that are going to be explained in the following section.

SMOTEBoost tries to reduce the bias from the learning procedure due to the class imbalance, and increase the sampling weight for the minority class. SMOTE [14] is introduced in each round of boosting, which enables each learner to be able to sample more of the minority class cases, and learn better and broader decision regions for the minority class.

It also brings the benefit of enhancing the probability of selection for the difficult minority class cases that are dominated by the majority class points [15]. The variation of boosting procedure of the SMOTEBoost process is a variant of the AdaBoost.M2 procedure [16].

RUSBoost [17] uses the AdaBoost.M2. The difference with SMOTEBoost is that RUSBoost applies Random Under Sampling instead of SMOTE. The application of SMOTE at this point has two drawbacks that RUSBoost is designed to overcome:

- It increases the complexity of the algorithm. SMOTE finds the k nearest neighbors of the minority class samples, and then extrapolates them to make new synthetic samples. RUS, on the other hand, simply deletes the majority class examples randomly.
- RUS produces less training data (as it is an undersampling technique, not like SMOTE, which is an oversampling technique). This can be translated into shorter model training times [17].

MetaCost [18] is a combination of bagging with cost-sensitive classification. The bagging part of the technique is used to relabel training data so that each training example is assigned a prediction that minimizes the expected cost for that instance. Based on the modified training data, MetaCost induces a new classifier which provides information about how a decision was reached.

2.3.5. Defect Prediction

Regarding the problem of software defect prediction, many techniques have been proposed in the literature - statistical methods (regression [19], and Support Vector Machines [20], etc.), machine learning (classification trees [21]), neural networks [22]), probabilistic models (Naïve Bayes [23] and Bayesian networks), ensembles of different techniques and meta-heuristics (ant colonies [24], etc). Despite this fact, some discrepancies are found:

- No classifier is consistently better than others.
- There is no optimum metric that allows the evaluation and comparison of classifiers ([23, 25, 26]).
- Data is also affected by quality issues - class imbalance, overlapping, outliers, etc.).

Some authors highlight the problem of imbalanced datasets when dealing with the project at hand, defect prediction (Seiffert et al. [27] and in Khoshgoftaar et al. [28]).

As it has been mentioned before, there is no classifier that behaves consistently better. No technique is able to give a an outstanding performance when evaluating classifiers. Some authors have compared performance of several measures (e.g., Peng [29], Peng et al. [30], this paper actually propose performance metrics to evaluate merit of classification algorithms and ranked classification algorithms, respectively).

Further analysis on the subject comes from the hand of Lessman et al. [31]. This paper compared several classifiers, discussing performance metrics such like TP_r and FP_r . But finally advocated to use the AUC⁶ as a good indicator for classifiers comparison. This results is known as sub-optimal for highly imbalanced datasets.

Arisholm et al. [?] compared different classification algorithms (tree algorithm (C4.5), coverage rule algorithm (PART), logistic regression, back-propagation neural networks and Support Vector Machines) over 13 different Java developed systems. They used three metrics to compare results:

- Object-oriented metrics.
- Churn (δ) metrics between successive releases.
- Process management metrics from a configuration management system.

The conclusion was that large differences can be achieved depending on the comparison criteria of the data. To solve this problem, the paper proposed a new AUC based, cost-effectiveness metric. Same approach has been evaluated and explored in Mende and Koschke [32].

⁶Further explained in Section 3.3.7, Area Under the ROC Curve

Chapter 3

Empirical Work

In this chapter, we cover the experimental work carried out. Firstly, we describe the datasets used for the experimentation; then, the supervised classifiers evaluated; the evaluation metrics chosen; and finally, present and discuss the results.

3.1. Datasets

In this work, publicly available datasets in the domain of Software defect prediction were used, were used, the Jureczko and Madeyski dataset ¹ [33, 34], the Apache dataset ([35]) and the Harman Search Base dataset [36].

From the first cluster of datasets, 15 open source projects are the ones chosen (a total of 8 are used for this project). The number of defects found in each class collected from the Software Management System (SCM) using a regular expression. The datasets are publicly available (can be found in the PROMISE repository [37]). These datasets have been used in previous researches, [38–40], which allows comparing and analyzing the obtained results.

A sample can be considered as *defective* when the number of defects inside the class is more than 0. Similarly, if the number of defects is 0, then the class is *non-defective*. This allows a binary classification, making easier handling results, operations and comparisons.

Table 3.1: Defect Metrics Dataset Variables

<i>Metric</i>	<i>Description</i>
WMC	Weighted methods per class [41]
DIT	Depth of Inheritance Tree [41]
NOC	Number of Children [41]
CBO	Coupling between object classes [41]
RFC	Response for a Class [41]
LCOM	Lack of cohesion in methods [41]
Ca	Afferent couplings [42]
Ce	Efferent couplings [42]
NPM	Number of Public Methods [43]

Continued on next page

¹<http://snow.iiar.pwr.wroc.pl:8080/MetricsRepo/>

Table 3.1 – Continued from previous page

<i>Metric</i>	<i>Description</i>
LCOM3	Lack of cohesion in methods [44]
LOC	Lines of Code [43]
DAM	Data Access Metric [43]
MOA	Measure of Aggregation [43]
MFA	Measure of Functional Abstraction [43]
CAM	Cohesion Among Methods of Class [43]
IC	Inheritance Coupling [45]
CBM	Coupling Between Methods [45]
AMC	Average Method Complexity [45]
MAX_CC	Maximum McCabe’s cyclomatic complexity [46]
AVG_CC	Average McCabe’s cyclomatic complexity [46]

There is another sole dataset obtained from the same source as the previous collection of datasets, with a very similar structure of data, the *Apache* dataset. It has the same origin and objective as its predecessors.

On the second cluster of datasets, the data comes from a total of 8 different Hadoop versions. Their original purpose is to train a search based fault prediction system.

Similarly to Jureczko and Madeyski dataset [33,34], it uses: (1) WMC, (2) DIT, (3), NOC, (4) CBO, (5) RFC, (6) LCOM, (7) NOM, and (8) LOC; metrics to define each dataset.

Regarding more information on the content of the datasets the next table (see Table 3.2) summarizes the number of samples on each dataset and further valuable information, such as the absolute and relative number of defects for those datasets.

Table 3.2: Description of the Datasets

<i>Project</i>	<i>Version</i>	<i>#instances</i>	<i>#Non-Defective</i>	<i>#Defective</i>	<i>%Defective</i>
ant	1.3	125	105	20	16.00
	1.4	178	138	40	22.47
	1.5	293	261	32	10.92
	1.6	351	259	92	26.21
	1.7	745	579	166	22.28
apache	-	191	107	84	43.98
camel	1.0	339	326	13	3.83
	1.2	608	392	216	35.52
	1.4	872	727	145	16.62
	1.6	965	777	188	19.48
hadoop	0.1	141	91	50	35.60
	0.2	191	149	42	21.99
	0.3	211	158	53	25.12
	0.4	201	159	42	20.90
	0.5	217	180	37	17.05

Continued on next page

Table 3.2 – Continued from previous page

<i>Project</i>	<i>Version</i>	<i>#instances</i>	<i>#Non-Def</i>	<i>#Def</i>	<i>%Def</i>
	0.6	234	203	31	13.25
	0.7	250	202	48	19.20
	0.8	240	224	16	6.67
ivy	1.4	241	225	16	6.63
	2.0	352	312	40	11.36
jedit	3.2	272	182	90	33.08
	4.0	306	231	75	24.50
	4.1	312	233	79	25.32
	4.2	367	319	48	13.07
	4.3	492	481	11	2.23
log4j	1.0	135	101	34	25.18
	1.1	109	72	37	33.94
	1.2	205	16	189	92.19
synapse	1.0	157	141	16	10.19
	1.1	222	162	60	27.02
	1.2	256	170	86	33.59
xalan	2.4	723	613	110	15.21
	2.5	803	416	387	48.19
	2.6	885	474	411	46.44
	2.7	909	11	898	98.78
xerces	1.2	440	369	71	16.13
	1.3	453	384	69	15.23
	1.4	588	151	437	74.31

The experiments of this paper use the latest version of the datasets *ant*, *apache*, *camel*, *hadoop*, *ivy*, *jedit*, *log4j*, *xalan* and *xerces*; alongside all the available versions of the *hadoop* dataset.

3.2. Supervised Classifiers

This work makes use of several supervised learning algorithms. The experiments carried out use the following algorithms:

Naive Bayes (NB) [47] is a classifier that works on conditional probabilities, uses the Bayes theorem to predict the class for each data input. Calculates the probability of a certain event, given prior knowledge. This classifier assigns a set of attributes a_1, \dots, a_n to a given class C so that the probability of the class description value of the attributes instances is maximal: $P(C|a_1, \dots, a_n)$. The probability of the hypothesis, given that the evidence is true, is the probability of the evidence, given the hypothesis is true, multiplied by the probability of the hypothesis; in relation to the probability of the evidence. See Eq. 3.1.

$$P(H|E) = \frac{(E|H) * P(H)}{P(E)} \quad (3.1)$$

For this project it has been selected the Gaussian Naive Bayes from `scikit-learn`² to perform the experimentation. Being *Gaussian* means that the likelihood of the features is assumed to be Gaussian. The formula is given by Eq. 3.2.

$$P(x_i|y) = \left(\frac{1}{\sqrt{2\pi\sigma_y^2}}\right) \exp\left(-\frac{(x_i - \mu_y)^2}{2\sigma_y^2}\right) \quad (3.2)$$

Decision Trees can be seen as rules with a root node, branches are conditions and leaves correspond to classes. There are many decision trees algorithm such as CART (Classification And Regression Trees) [48] is a non-parametric decision tree, similar to **C4.5** [49].

CART constructs a two branch bifurcation of the most discriminating attribute, based on the Gini index. It can generate either classification or regression trees - depends on the variable (categorical or numeric, respectively). The implementation available in `scikit-learn` [50]³ is an optimised version of this algorithm, although it does not support categorical variables.

Nearest Centroid classifier[51], **Nearest Prototype** classifier, or **Rocchio classifier** for its similarity to an algorithm with the same name (see Eq.3.3).

$$\vec{Q}_m = (a \cdot \vec{Q}_o) + (b \cdot \frac{1}{|D_r|} \cdot \sum_{\vec{D}_j \in D_r} \vec{D}_j) - (c \cdot \frac{1}{|D_{nr}|} \cdot \sum_{\vec{D}_k \in D_{nr}} \vec{D}_k) \quad (3.3)$$

The labels of a given sample are assigned by evaluating the classes of training samples whose mean is closest to the evaluated point. The training procedure, given a labeled training set $(\vec{x}_1, y_1), \dots, (\vec{x}_n, y_n)$ with class labels $y_i \in Y$, compute the per-class centroid with Eq. 3.4.

$$\vec{\mu}_l = \frac{1}{|C_l|} \sum_{i \in C_l} \vec{x}_i \quad (3.4)$$

where C_l is the set of indices of samples belonging to class $l \in Y$. The prediction functions, takes the class assigned to an observation \vec{x} is Eq. 3.5.

$$\vec{y} = \underset{l \in Y}{\operatorname{argmin}} ||\vec{\mu}_l - \vec{x}|| \quad (3.5)$$

3.3. Evaluation Metrics

Part of the process of applying a classification algorithm is to measure the success and the results of the training. In order to do it, some metrics can be calculated out of the testing to the trained classifier. Here is where the Confusion Matrix comes at hand. The Confusion Matrix (see Table 3.3) allows us to summarize the performance of a given classification algorithm, it is also the foundation of many of the performance metrics used in classification by:

True Positive (TP) - Data is correctly classified as positive.

True Negative (TN) - Data is correctly classified as negative.

False Positive (FP) - Data being negative classified as positive.

²https://scikit-learn.org/stable/modules/generated/sklearn.naive_bayes.GaussianNB.html

³<https://scikit-learn.org/stable/modules/tree.html>

Table 3.3: Confusion Matrix for Binary Classification

		<i>Actual Class</i>	
		<i>Positive</i>	<i>Negative</i>
<i>Predicted Class</i>	<i>Positive</i>	True Positive (<i>TP</i>)	False Positive (<i>FP</i>)
	<i>Negative</i>	False Negative (<i>FN</i>)	True Negative (<i>TN</i>)

False Negative (FN) - Data being positive classified as negative.

These specifications indicate that the input data should have a binary target: one value that can be classified as *positive* and a second value that can be classified as negative. From this statistical classification ⁴, many performance measures can be calculated. Some of the most widely used metrics, and the ones used in this paper are explained next.

3.3.1. Precision

Also know as Positive Predictive Value (PPV). It is the relation between the *true positives* calculated and the overall positives detected by the classification algorithm (see Eq. 3.6).

$$PPV = \frac{TP}{TP + FP} = 1 - FDR \quad (3.6)$$

3.3.2. Recall

Also known as sensitivity, hit rate, or True Positive Rate (TPR). It stands for the relation between the *true positives* calculated and the real number of positives (see Eq. 3.7).

$$TPR = \frac{TP}{P} = \frac{TP}{TP + FN} = 1 - FNR \quad (3.7)$$

3.3.3. Fall-out

Also called False Positive Rate (FPR). It is the probability of rejecting (falsely) the null hypothesis⁵ for a particular test (see Eq. 3.8).

$$FPR = \frac{FP}{N} = \frac{FP}{FP + TN} = 1 - TNR \quad (3.8)$$

3.3.4. Balance Accuracy

It goes by the acronym BA. It is a metric generally used to evaluate how good is a (binary) classifier. It is a measure that comes in specially handy for imbalanced datasets. Its formula is represented by the mean of *sensitivity* and *specificity* (see Eq. 3.9).

$$BA = \frac{TPR + TNR}{2} \quad (3.9)$$

⁴Also know as error matrix.

⁵General statement or default position that there is no relationship between two measured phenomena or no association among groups.

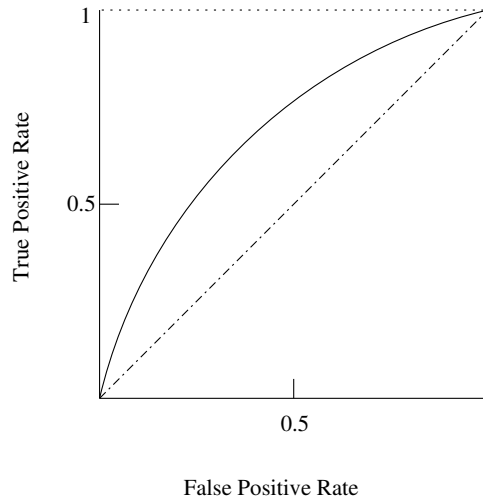


Figure 3.1: ROC Curve

3.3.5. F-Measure

Also known as F_1 , or *Sørensen-Dice coefficient* (independently developed by Sørensen [52] and Dice [53]) is the harmonic mean of precision and sensitivity, the two previous measures, which measures accuracy (see Eq. 3.10). It is twice the relation of the multiplication between *recall* and *precision* and their addition. It is commonly used in highly imbalanced datasets but there are also some criticisms as it does not take into account the *True Negative* (TN) cases.

$$F_1 = 2 \cdot \frac{PPV \cdot TPR}{PPV + TPR} = \frac{2 \cdot TP}{2 \cdot TP + FP + FN} \quad (3.10)$$

3.3.6. MCC

The Matthews Correlation Coefficient (MCC) [54] or *phi* coefficient measures the quality of a binary classification robust to the imbalance problem (Eq. 3.11). Its range values are between -1 and +1, where -1 represents complete inconsistency (disagreement), 0 indicates that the prediction is no better than a random prediction; and +1 would be a perfect prediction.

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (3.11)$$

3.3.7. Receiver Operating Characteristic Curve

The Receiver Operating Characteristic (ROC)[55] Curve represents graphically the True Positive Rate (TPR) versus the False Positive Rate (FPR) as shown in Figure 3.1.

Once the curve is plotted, the more the curve gets similar to a slope of $TPR = FPR$ the more imbalance that can be found in the dataset. It provides graphical visualization of the results.

The Area Under the ROC Curve (AUC) is a quality measure between positive and negative rates with a single value. This metric allows to compare models.

An approximation to the function can be calculated with Eq 3.12.

$$AUC = \frac{1 + TP_r - FP_r}{2} \quad (3.12)$$

Typically, three unbiased metrics, i.e., AUC, F-score ([52, 53]), Matthews Correlation Coefficient (MCC - [54]), are used to evaluate the performance on imbalanced datasets. Other measures cannot be used when data is highly imbalanced, like *accuracy* (*Acc*) (defined by Eq. 3.13), as it does not take into account the number of labels of different classes.

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (3.13)$$

3.4. Results and discussion

3.4.1. Methodology

To answer the research questions stated in Section 1.2, we run several experiments. First, we analyse the complexity metrics (see Section 2.1) from all selected datasets (see Section 3.1). Then, we retrieve some analytical metrics (see Section 3.3), applying *K*-fold Cross Validation to those datasets. Finally, we repeat the process applying some under/oversampling techniques with *K*-CV (see Sections 2.3.1.1 and 2.3.1.2, respectively).

As the final aim is to see how complexity metrics affect classification and therefore the analytical metrics, a final section is going to summarize the results obtained and the conclusions drawn out of those measures and answer the research questions.

3.4.2. Data Complexity Metrics Analysis

As it has been mentioned in *Data Complexity Metrics* (see Section 2.1), the software package to calculate them is available in R, ECoL⁶. Therefore, it was necessary to call it from the Python environment. In order to do so, the package RServe, a client server implementation for R workspace to execute functions from other environments like Python, was used. In other words, this is a connector that allow us to execute the ECoL complexity metrics functions. The source code regarding this connector can be found in the Appendix B, Section B.1.

The rest of the experimental work was implemented in a Python script. The structure of the script tries to find and compare the complexity metrics obtained from different datasets to see if there is a certain relation between metrics. To do so, a script was developed (see Algorithm 1) to connect Python to the ECoL library in R and returns the complexity metrics of a certain dataset (see its full implementation in Appendix B, Section B.4).

Algorithm 1 Datasets Complexity Metrics Comparison

Require: \mathcal{D} dataset

Ensure: \mathcal{C} complexity metrics

```

1: con ← connectEcol()
2: for all set in  $\mathcal{D}$  do
3:   inputs, targets ← getDataset(set)
4:   metrics ← con.getMetrics(inputs, targets)
5:    $\mathcal{C}$ .add(metrics)
6: end for
7: plotComparison( $\mathcal{C}$ )

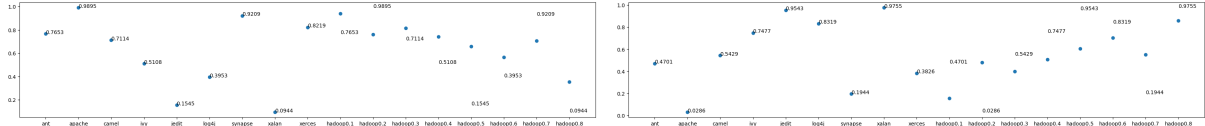
```

⁶<https://github.com/lpfgarcia/ECoL/>

The results are also stored in CSV files, which are represented as Tables C.1 and C.2.

The experiment has been repeated for two independent sets of datasets (see Section 3.1 for more details regarding the datasets and their content). The first experiment results are summarized in Table C.1, whereas the second experiment, regarding the Hadoop datasets is shown in Table C.2.

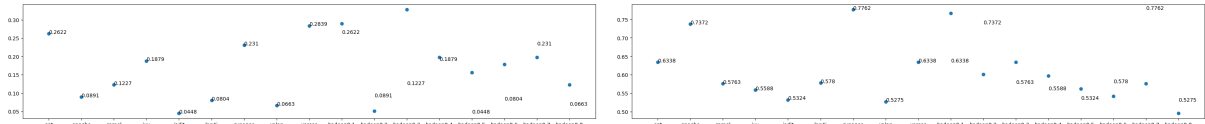
The obtained results are also showed in the following Figures: (3.2) balance, (3.3) correlation, (3.4) dimensionality, (3.5) linearity, (3.6) neighborhood, (3.7) network, (3.8) overlap, and (3.9) smoothness.



(a) Balance C1

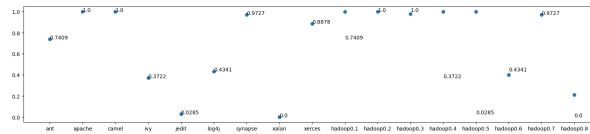
(b) Balance C2

Figure 3.2: Balance Measures



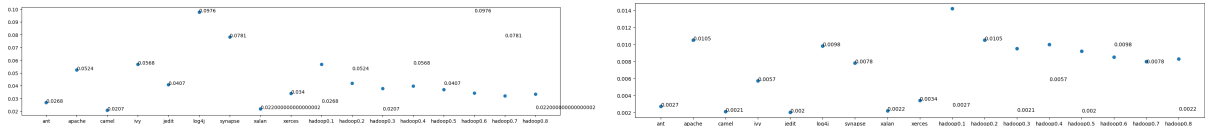
(a) Correlation C2

(b) Correlation C3



(c) Correlation C4

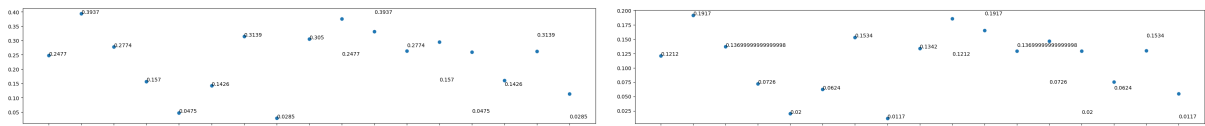
Figure 3.3: Correlation Measures



(a) Dimensionality T2

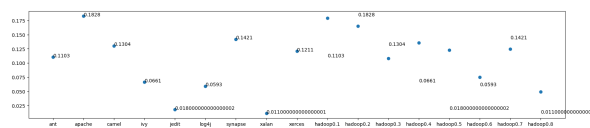
(b) Dimensionality T3

Figure 3.4: Dimensionality Measures



(a) Linearity L1

(b) Linearity L2



(c) Linearity L3

Figure 3.5: Linearity Measures

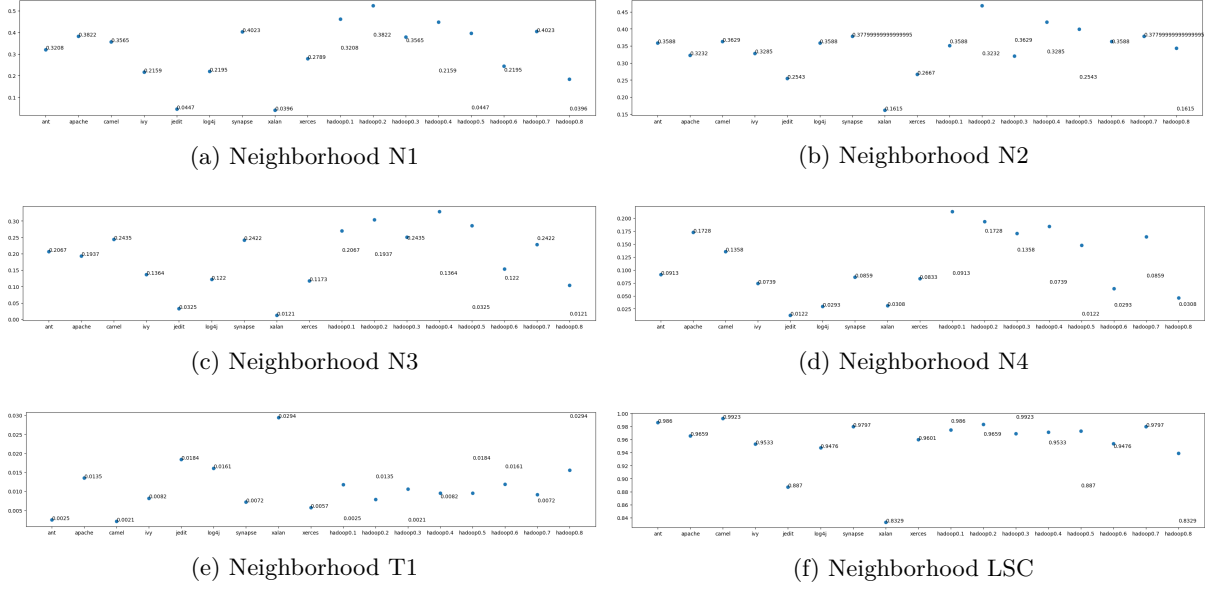


Figure 3.6: Neighborhood Measures

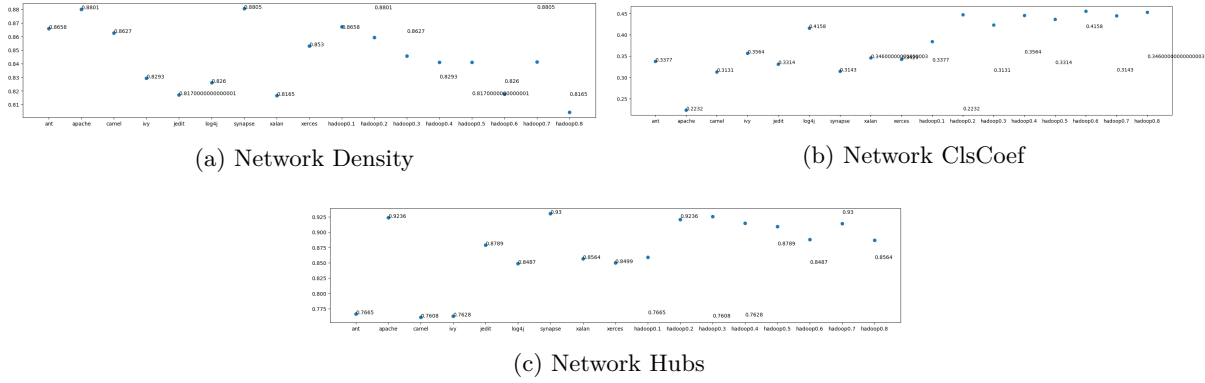


Figure 3.7: Network Measures

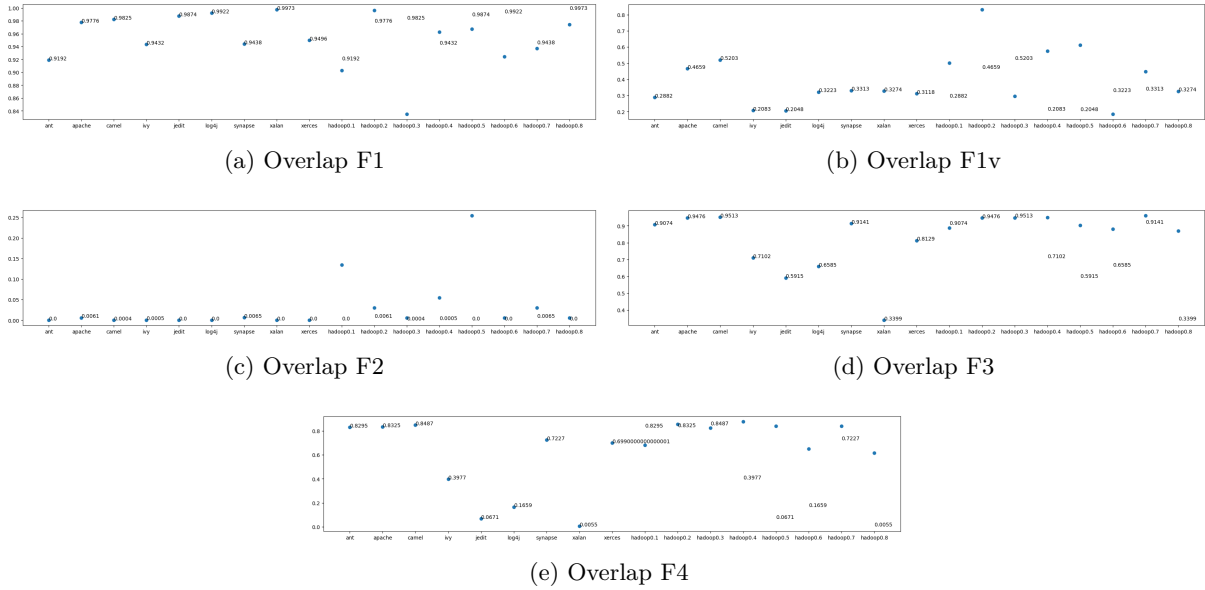


Figure 3.8: Overlap Measures

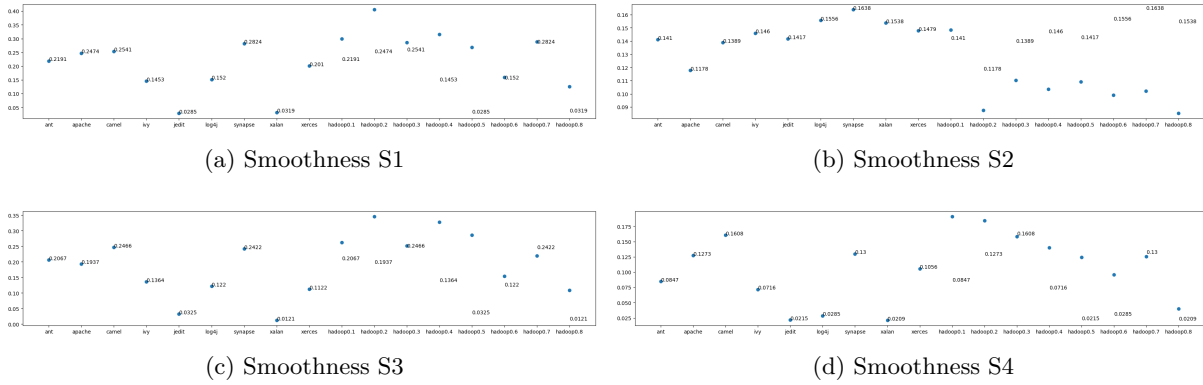


Figure 3.9: Smoothness Measures

This way it is easier to compare results through datasets and metrics. To see the whole extent of the numerical values, see the tables at Appendix C. The data is summarized in tables C.1 and C.2. To see the images in more detail (bigger) go to Appendix D, Section D.1.

Further results are compared and discussed in Section 3.4.5.

3.4.3. Cross Validation Analysis

This experiment tries to find the impact of applying the K -fold Cross-Validation. It is a widely extended technique in data science that brings a solution to the problem of performing testing to a data set with no separate training data - the same instances in a given dataset should not be used for both training and testing a classifier at the same time, instead data can be divided so a portion is used for training and another separate portion for testing/validation. Cross validation allows us to estimate the performance of the model trained by the whole dataset dividing it into k folds as follows:

- Training set which is known data by the classifier, and used to train it. It represents $k - 1/k$ parts of the original set.
- Testing set, also known as validation set which corresponds to unseen data for trained classifier used to test its performance. It usually is $1/k$ of the original dataset.

Then, the average of carrying out k iterations, same as the number of folds (parts/divisions) of the dataset, is calculated. On each iteration, the *testing set* is rotated to another unused fold⁷ of the data - no testing set is repeated, which means that each fold is used only once for *testing* purposes.

The most common values for k (folds) used in data science are 5 and 10. For this experiment, k has been selected as $k = 5$, as a common value of k was needed for all experiments and some of the datasets did not have enough samples for a larger value of k .

The algorithm that analyses the performance of each fold and the calculates the mean performance can be simplified as the one explained in the Algorithm 2.

Algorithm 2 Metrics Analysis on K-fold

Require: \mathcal{D} dataset

- 1: inputs, targets $\leftarrow \mathcal{D}$
 - 2: $k \leftarrow 5$
 - 3: $kf \leftarrow \text{kfold}(k)$
-

⁷The data in the different folds does not change throughout the cross validation process.

```

4: splits  $\leftarrow$  kf.split(inputs)
5: for all  $train_i, test_i$  in splits do
6:    $x_{train}, x_{test} \leftarrow$  inputs.get( $train_i$ ), inputs.get( $test_i$ )
7:    $y_{train}, y_{test} \leftarrow$  targets.get( $train_i$ ), targets.get( $test_i$ )
8:    $clf \leftarrow$  trainNetwork( $x_{train}, y_{train}$ )
9:   confusionMatrix( $x_{test}, y_{test}, clf$ )
10: end for
11: calculateMeanPerformance( $clf$ )

```

The Python script used for this experiment can be found in Appendix B, Section B.4. It basically separates a dataset into folds and calculates the performance metrics for each fold, to later on compute the mean value of those metrics for the entire dataset.

With the *confusion matrix* other metrics are calculated such as *recall*, *MCC*, etc. Those metrics are then compared in Tables 3.4 and 3.5, for each specific dataset (to see the full extent of the comparison we refer to Section 3.4.5. For the sake of simplicity, only two tables of the aforementioned resulting datasets. Table 3.4 shows the results obtained from Apache dataset.

Table 3.4: Cross-Validation Results — Apache Dataset

<i>Fold</i>	<i>Function</i>	<i>Precision</i>	<i>Recall</i>	<i>Fall Out</i>	<i>Balanced</i>	<i>F1</i>	<i>MCC</i>	<i>AUC</i>
1	Naive Bayes	0.4286	0.1579	0.200	0.4789	0.2308	-0.0548	0.4789
	Decision Tree	0.8235	0.7368	0.1500	0.7934	0.7778	0.5915	0.7934
	Nearest Centroid	0.3333	0.3158	0.6000	0.3579	0.3243	-0.2850	0.3579
2	Naive Bayes	0.5000	0.0800	0.1538	0.4631	0.1379	-0.1142	0.4631
	Decision Tree	0.8095	0.6800	0.3077	0.6862	0.7391	0.3552	0.6862
	Nearest Centroid	0.5000	0.1600	0.3077	0.4262	0.2424	-0.1719	0.4262
3	Naive Bayes	0.5000	0.0909	0.1250	0.4830	0.1538	-0.0548	0.4830
	Decision Tree	0.8462	0.5000	0.1250	0.6875	0.6286	0.3903	0.6875
	Nearest Centroid	0.4000	0.1818	0.3750	0.4034	0.2500	-0.2166	0.4034
4	Naive Bayes	0.3333	0.8182	0.6667	0.5758	0.4737	0.1515	0.5758
	Decision Tree	0.5833	0.6364	0.1852	0.7256	0.6087	0.4402	0.7256
	Nearest Centroid	0.8000	0.7273	0.0741	0.8266	0.7619	0.6727	0.8266
5	Naive Bayes	0.3043	1.0000	0.5161	0.7419	0.4667	0.3838	0.7419
	Decision Tree	0.5000	1.0000	0.2258	0.8871	0.6667	0.6222	0.8871
	Nearest Centroid	0.4545	0.7143	0.1935	0.7604	0.5556	0.4451	0.7604
Mean	Naive Bayes	0.4132	0.4294	0.3323	0.5485	0.2926	0.0623	0.5485
	Decision Tree	0.7125	0.7106	0.1987	0.7560	0.6842	0.4799	0.7560
	Nearest Centroid	0.4976	0.4198	0.3101	0.5549	0.4268	0.0889	0.5549

The second example shown in Table 3.5 was obtained on the experiment performed over the Hadoop (v0.8) dataset.

Table 3.5: Cross-Validation Results — Hadoop 0.8 Dataset

<i>Fold</i>	<i>Function</i>	<i>Precision</i>	<i>Recall</i>	<i>Fall Out</i>	<i>Balanced</i>	<i>F1</i>	<i>MCC</i>	<i>AUC</i>
1	Naive Bayes	1.0000	0.1250	0.0000	0.5625	0.2222	0.3262	0.5625
	Decision Tree	0.0000	0.0000	0.0250	0.4875	0.0000	-0.0652	0.4875
	Nearest Centroid	0.1667	1.0000	1.0000	0.5000	0.2857	0.0000	0.5000
2	Naive Bayes	0.0000	0.0000	0.1064	0.4468	0.0000	-0.0497	0.4468
	Decision Tree	0.0000	0.0000	0.1064	0.4468	0.0000	-0.0497	0.4468
	Nearest Centroid	0.0208	1.0000	1.0000	0.5000	0.0408	0.0000	0.5000
3	Naive Bayes	0.0000	0.0000	0.0851	0.4574	0.0000	-0.0440	0.4574
	Decision Tree	0.0000	0.0000	0.0851	0.4574	0.0000	-0.0440	0.4574
	Nearest Centroid	0.0208	1.0000	1.0000	0.5000	0.0408	0.0000	0.5000
4	Naive Bayes	0.3333	0.2500	0.0455	0.6023	0.2857	0.2335	0.6023
	Decision Tree	0.0000	0.0000	0.0426	0.4787	0.0000	-0.0304	0.4787
	Nearest Centroid	0.0000	0.0000	0.0227	0.4886	0.0000	-0.0440	0.4886
5	Naive Bayes	0.0000	0.0000	0.0000	0.5000	0.0000	0.0000	0.5000
	Decision Tree	0.0000	0.0000	0.0000	0.5000	0.0000	0.0000	0.5000
	Nearest Centroid	0.0000	0.0000	0.0000	0.5000	0.0000	0.0000	0.5000
Mean	Naive Bayes	0.26667	0.0750	0.0474	0.5138	0.1016	0.0932	0.5138
	Decision Tree	0.0000	0.0000	0.0484	0.4758	0.0000	-0.0446	0.4758
	Nearest Centroid	0.0417	0.6000	0.6045	0.4977	0.0735	-0.0088	0.4977

The inner results of each fold are not evaluated when analyzing the results of the experiments, but that data could be used to understand how data metrics (including imbalance) affect classification. The objective evaluated in this paper is to see if the metrics obtained for each dataset have any relation with the performance of the classifiers.

3.4.4. Imbalance Experimental Work

After experimenting with cross-validation, we now focus on if filters applied to the dataset have any effect on the quality of the trained classifier. In this case, it is carried out by applying imbalance filters to the folds in the datasets (see Section 2.3 for more information on imbalance filters). Here, the following techniques were used in the experiments:

Undersampling Removing samples from majority class.

Oversampling Creating new samples in the minority class.

3.4.4.1. Undersampling with Cross Validation

For this experiment, one undersampling algorithm is applied (2.3.1.1) to see how folds are affected by removing majority class samples, and therefore, looking at how it impacts the classification algorithm.

The undersampling technique is not done on the whole dataset in advance, only the training folds are the ones that the undersampling algorithm is applied.

The k value chosen for cross validation is $k = 5$. A simplification of the procedure followed by this experiment can be found in the Algorithm 3.

Algorithm 3 Undersampling with Cross-Validation**Require:** \mathcal{D} dataset

```

1: inputs, targets  $\leftarrow \mathcal{D}$ 
2: k  $\leftarrow 5$ 
3: kf  $\leftarrow$  kfold(k)
4: splits  $\leftarrow$  kf.split(inputs)
5: samplingStrategy  $\leftarrow$  0:50, 1:50  $\triangleright$  Binary class with a post undersampling distribution of 50-50
6: randomState  $\leftarrow 42$ 
7: for all  $train_i, test_i$  in splits do
8:    $x_{train}, x_{test} \leftarrow$  inputs.get( $train_i$ ), inputs.get( $test_i$ )
9:    $y_{train}, y_{test} \leftarrow$  targets.get( $train_i$ ), targets.get( $test_i$ )
10:  X, Y = makeImbalance(
11:     $x_{train}, y_{train},$ 
12:    samplingStrategy,
13:    randomState
14:  )
15:  clf  $\leftarrow$  classifier(NearMiss(2), GaussianNB())
16:  clf  $\leftarrow$  trainNetwork(X, Y)
17:  confusionMatrix( $x_{test}, y_{test},$  clf)
18: end for
19: calculateMeanPerformance(clf)

```

Similarly to the previous experiment, the following classification algorithms were used to measure performance of the alterations done on the dataset, i.e., (1) Naive Bayes (Gaussian), (2) Decision Tree and (3) kNN Nearest Centroid.

The experiment creates the same tables obtained in experiment 3.4.3, that is why sharing all the resulting tables of this experiment would be unnecessary - the results evaluated here can be found in Section 3.4.5. That is why only two of them have been included into this dissertation. The Apache dataset experiment (see Table 3.6).

Table 3.6: Cross-validation with Undersampling Results — Apache dataset

<i>Fold</i>	<i>Function</i>	<i>Precision</i>	<i>Recall</i>	<i>Fall Out</i>	<i>Balanced</i>	<i>F1</i>	<i>MCC</i>	<i>AUC</i>
1	Naive Bayes	0.5556	0.8824	0.5455	0.6684	0.6818	0.3620	0.6684
	Decision Tree	0.7000	0.8235	0.2727	0.7754	0.7568	0.5464	0.7754
	Nearest Centroid	0.4167	0.2941	0.3182	0.4880	0.3448	-0.0259	0.4880
2	Naive Bayes	0.5500	0.7333	0.3913	0.6710	0.6286	0.3348	0.6710
	Decision Tree	0.5500	0.7333	0.3913	0.6710	0.6286	0.3348	0.6710
	Nearest Centroid	0.3571	0.3333	0.3913	0.4710	0.3448	-0.0587	0.4710
3	Naive Bayes	0.7586	0.8800	0.5385	0.6708	0.8148	0.3811	0.6708
	Decision Tree	0.8421	0.6400	0.2308	0.7046	0.7273	0.3883	0.7046
	Nearest Centroid	0.7000	0.2800	0.2308	0.5246	0.4000	0.0530	0.5246
4	Naive Bayes	0.6667	0.7273	0.1481	0.7896	0.6957	0.5650	0.7896
	Decision Tree	0.6667	0.7273	0.1481	0.7896	0.6957	0.5650	0.7896
	Nearest Centroid	0.3077	0.3636	0.3333	0.5152	0.3333	0.0290	0.5152

Continued on next page

Table 3.6 – *Continued from previous page*

<i>Fold</i>	<i>Function</i>	<i>Precision</i>	<i>Recall</i>	<i>Fall Out</i>	<i>Balanced</i>	<i>F1</i>	<i>MCC</i>	<i>AUC</i>
5	Naive Bayes	0.5000	0.5625	0.4091	0.5767	0.5294	0.1517	0.5767
	Decision Tree	0.6316	0.7500	0.3182	0.7159	0.6857	0.4264	0.7159
	Nearest Centroid	0.5556	0.3125	0.1818	0.5653	0.4000	0.1518	0.5653
Mean	Naive Bayes	0.5928	0.6662	0.3917	0.6372	0.6059	0.2992	0.6372
	Decision Tree	0.6781	0.7348	0.2722	0.7313	0.6988	0.4522	0.7313
	Nearest Centroid	0.4674	0.3167	0.2911	0.5128	0.3646	0.0298	0.5128

And the result obtained on the same experiment for the Hadoop (v0.8) experiment (see Table 3.7).

Table 3.7: Cross-validation with Undersampling Results — Hadoop 0.8

<i>Fold</i>	<i>Function</i>	<i>Precision</i>	<i>Recall</i>	<i>Fall Out</i>	<i>Balanced</i>	<i>F1</i>	<i>MCC</i>	<i>AUC</i>
1	Naive Bayes	0.1429	0.5000	0.1304	0.6848	0.2222	0.2092	0.6848
	Decision Tree	0.1053	1.0000	0.3696	0.8152	0.1905	0.2576	0.8152
	Nearest Centroid	0.0345	0.5000	0.6087	0.4457	0.0645	-0.0444	0.4457
2	Naive Bayes	0.0000	0.0000	0.2667	0.3667	0.0000	-0.1491	0.3667
	Decision Tree	0.0833	0.3333	0.2444	0.5444	0.1333	0.0497	0.5444
	Nearest Centroid	0.0952	0.6667	0.4222	0.6222	0.1667	0.1193	0.6222
3	Naive Bayes	0.0833	0.5000	0.2391	0.6304	0.1429	0.1204	0.6304
	Decision Tree	0.0000	0.0000	0.3261	0.3370	0.0000	-0.1406	0.3370
	Nearest Centroid	0.0000	0.0000	0.4348	0.2826	0.0000	-0.1762	0.2826
4	Naive Bayes	0.1333	0.3333	0.3095	0.5119	0.1905	0.0170	0.5119
	Decision Tree	0.1765	0.5000	0.3333	0.5833	0.2609	0.1153	0.5833
	Nearest Centroid	0.0625	0.1667	0.3571	0.4048	0.0909	-0.1336	0.4048
5	Naive Bayes	0.0000	0.0000	0.1556	0.4222	0.0000	-0.1067	0.4222
	Decision Tree	0.2000	0.6667	0.1778	0.7444	0.3077	0.2914	0.7444
	Nearest Centroid	0.0000	0.0000	0.2444	0.3778	0.0000	-0.1408	0.3778
Mean	Naive Bayes	0.0719	0.2667	0.2203	0.5232	0.1111	0.0182	0.5232
	Decision Tree	0.1130	0.5000	0.2902	0.6049	0.1785	0.1147	0.6049
	Nearest Centroid	0.0384	0.2667	0.4134	0.4266	0.0644	-0.0751	0.4266

As it has been mentioned in Section 2.3.1.1, there are several versions of *Near Miss* algorithm. For this experiment it was used *version 2*. This undersampling algorithm selects the majority class samples with the least average distance to the 3 farthest minority class samples.

The analysis of the metrics obtained are discussed in Section 3.4.5.

3.4.4.2. Oversampling with Cross Validation

In this experiment, similarly to Section 3.4.4.1, an imbalance filter is used. In this case, the oversampling technique is implemented and is later on compared to other experiment results (see Section 3.4.5).

The technique has been applied to the different folds of the dataset, not to the entire data. Once again, the dataset is divided into $k = 5$ folds.

The logic of the Python code experiment is summarized in Algorithm 4. The difference with the undersampling Algorithm 3 is that uses the SMOTE technique (see Section 2.3.1.2) instead of *Near Miss* undersampling technique.

Algorithm 4 Oversampling and K-fold on classification performance

Require: \mathcal{D} dataset

```

1: inputs, targets  $\leftarrow \mathcal{D}$ 
2:  $k \leftarrow 5$ 
3:  $kf \leftarrow \text{kfold}(k)$ 
4: splits  $\leftarrow kf.\text{split}(\text{inputs})$ 
5: for all  $train_i, test_i$  in splits do
6:    $x_{train}, x_{test} \leftarrow \text{inputs.get}(train_i), \text{inputs.get}(test_i)$ 
7:    $y_{train}, y_{test} \leftarrow \text{targets.get}(train_i), \text{targets.get}(test_i)$ 
8:    $clf \leftarrow \text{classifier}(\text{SMOTE}(), \text{GaussianNB}())$ 
9:    $clf \leftarrow \text{trainNetwork}(x_{train}, y_{train})$ 
10:  confusionMatrix( $x_{test}, y_{test}, clf$ )
11: end for
12: calculateMeanPerformance( $clf$ )

```

The classifiers used for this experiment are - (1) Naive Bayes (Gaussian); (2) Decision Tree; and (3) kNN Nearest Centroid.

Next we show two of the results obtained, the first one is the result on the Apache dataset (see Table 3.8).

Table 3.8: Oversampling with Cross Validation Results — Apache dataset

<i>Fold</i>	<i>Function</i>	<i>Precision</i>	<i>Recall</i>	<i>Fall Out</i>	<i>Balanced</i>	<i>F1</i>	<i>MCC</i>	<i>AUC</i>
1	Naive Bayes	0.4286	0.1579	0.2000	0.4789	0.2308	-0.0548	0.4789
	Decision Tree	0.7222	0.6842	0.2500	0.7171	0.7027	0.4354	0.7171
	Nearest Centroid	0.3333	0.3158	0.6000	0.3579	0.3243	-0.2850	0.3579
2	Naive Bayes	0.5000	0.0800	0.1538	0.4631	0.1379	-0.1142	0.4631
	Decision Tree	0.8889	0.6400	0.1538	0.7431	0.7442	0.4619	0.7431
	Nearest Centroid	0.5000	0.1600	0.3077	0.4262	0.2424	-0.1719	0.4262
3	Naive Bayes	0.5000	0.0909	0.1250	0.4830	0.1538	-0.0548	0.4830
	Decision Tree	0.8000	0.5455	0.1875	0.6790	0.6486	0.3616	0.6790
	Nearest Centroid	0.4286	0.1364	0.2500	0.4432	0.2069	-0.1447	0.4432
4	Naive Bayes	0.3333	0.8182	0.6667	0.5758	0.4737	0.1515	0.5758
	Decision Tree	0.5385	0.6364	0.2222	0.7071	0.5833	0.3959	0.7071
	Nearest Centroid	0.6000	0.5455	0.1481	0.6987	0.5714	0.4092	0.6987
5	Naive Bayes	0.3182	1.0000	0.4839	0.7581	0.4828	0.4052	0.7581
	Decision Tree	0.5000	1.0000	0.2258	0.8871	0.6667	0.6222	0.8871
	Nearest Centroid	0.4545	0.7143	0.1935	0.7604	0.5556	0.4451	0.7604
Mean	Naive Bayes	0.4160	0.4294	0.3259	0.5518	0.2958	0.0666	0.5518
	Decision Tree	0.6899	0.7012	0.2079	0.7467	0.6691	0.4554	0.7467
	Nearest Centroid	0.4633	0.3744	0.2999	0.5373	0.3801	0.0505	0.5373

The second example is the one from the Hadoop (v0.8) experiment (see Table 3.9).

Table 3.9: Oversampling with Cross-Validation Results — Hadoop 0.8 dataset

<i>Fold</i>	<i>Function</i>	<i>Precision</i>	<i>Recall</i>	<i>Fall Out</i>	<i>Balanced</i>	<i>F1</i>	<i>MCC</i>	<i>AUC</i>
1	Naive Bayes	0.1176	0.2500	0.3750	0.4375	0.1600	-0.0974	0.4375
	Decision Tree	0.2500	0.1250	0.0750	0.5250	0.1667	0.0674	0.5250
	Nearest Centroid	0.1667	1.0000	1.0000	0.5000	0.2857	0.0000	0.5000
2	Naive Bayes	0.1000	1.0000	0.1915	0.9043	0.1818	0.2843	0.9043
	Decision Tree	0.0000	0.0000	0.4468	0.2766	0.0000	-0.1286	0.2766
	Nearest Centroid	0.0208	1.0000	1.0000	0.5000	0.0408	0.0000	0.5000
3	Naive Bayes	0.0000	0.0000	0.1915	0.4043	0.0000	-0.0701	0.4043
	Decision Tree	0.0000	0.0000	0.1064	0.4468	0.0000	-0.0497	0.4468
	Nearest Centroid	0.0208	1.0000	1.0000	0.5000	0.0408	0.0000	0.5000
4	Naive Bayes	0.0667	0.5000	0.6364	0.4318	0.1176	-0.0778	0.4318
	Decision Tree	0.2500	0.2500	0.0682	0.5909	0.2500	0.1818	0.5909
	Nearest Centroid	0.0000	0.0000	0.0000	0.5000	0.0000	0.0000	0.5000
5	Naive Bayes	0.0000	0.0000	0.0000	0.5000	0.0000	0.0000	0.5000
	Decision Tree	0.0000	0.0000	0.0435	0.4783	0.0000	-0.0435	0.4783
	Nearest Centroid	0.0000	0.0000	0.0000	0.5000	0.0000	0.0000	0.5000
Mean	Naive Bayes	0.0569	0.3500	0.2789	0.5356	0.0919	0.0078	0.5356
	Decision Tree	0.1000	0.0750	0.1480	0.4635	0.0833	0.0055	0.4635
	Nearest Centroid	0.0417	0.6000	0.6000	0.5000	0.0735	0.0000	0.5000

The analysis of the metrics obtained are in Section 3.4.5.

3.4.5. Comparison of the Results and Discussion

In this section, we analyze the results from the previous experiments. These are shown in Tables 3.10, 3.11 and 3.12. The RQ were as follows:

- RQ1 How complexity metrics are correlated to the outcome of supervised algorithms?
- RQ2 How complexity metrics and imbalance are related?
- RQ3 Do complexity metrics tell us something about the quality of the datasets?

To answer the RQ1 (see Section 3.4.5) we need to observe, for example, the values from *overlapping*. We assume that there is a certain correlation between overlapping and the classifiers' performance. For most cases in our experimentation, the higher the overlapping rate, the less efficient the classifier becomes. In this work, this assumption is not backed up by any statistical test, but just looking at the results.

For example, looking at the *overlapping* measures, when *overlapping F1* is higher than 0.90, almost none of the classifiers is able to surpass 0.5 in *precision* score, something similar happens with the *recall* and *fall-out* scores (all three measures indicate on a relative value how many input samples are

correctly predicted). It makes sense once to assume that the more interlaced the samples are (the more *overlapping*), the harder for a classifier to correctly predict its class.

In a similar way, its *linearity* measures are also directly related to the performance of the classification algorithms. Having high *overlapping* measures means that the *linearity* should be smaller (it is harder to separate data using a linear function if data is interlaced). Therefore, the higher the *linearity* measures obtained, the higher the performance should be. As all the selected datasets seem to have high *overlapping* values.

A third complexity metric that should be taken into account, regarding classifiers performance, is *balance* - (RQ1 and RQ2, 3.4.5 and 3.4.5, respectively). Its measures try to approximate the level of imbalance of a certain class. Therefore, the higher the measures' values, the greater should be the gap between the number of samples from the majority and minority class (all the datasets work with binary classes).

It can be observed that with large values of imbalance, not only the results have poor performance (less than 0.7 of *precision*, and similarly with *recall* and *fall-out* measures), but it also means that the different classifiers have very different results on the same dataset. This can be translated as, the performance on certain classifiers might depend on the imbalance of a certain dataset (RQ2 - see 3.4.5).

Taking a look at *Balanced Accuracy* measure (useful for imbalanced datasets, it can be observed that most of the classifiers do not behave as they should in either the positive or negative prediction. In example, all of the Hadoop datasets, where the imbalance ratio (*balance* measures) is not ideal, and the overlapping is too high.

Therefore, *MCC*, as a measure to see the quality of a binary classifier should also be low - just like in the Hadoop datasets. As for this last observation, it could be assumed that filters that would reduce imbalance, should also be able to increase the performance of the classifiers.

After some experimentation regarding this matter, no clear improvements have been noticed in any of the analytical measures. Furthermore, undersampling seems not to be a good technique when the number of samples is too low, as the number of samples in the resulting training dataset is not enough to obtain a good classifier. In some cases, it even reduces the performance.

After using SMOTE oversampling technique, the *Balanced Accuracy* metric seems to indicate that the classifier identified slightly better some of the testing data samples, but the resulting classifier still does not meet the desired quality (*MCC*).

In general, it seems that the techniques applied do not seem to fix perfectly the problems arose from either imbalance or overlapped datasets. This topic is going to be further discussed in Section 4, as well as some other remarks about the selected classifiers and possible further experimentation on this topic.

On trying to answer the final RQ3, *Do complexity metrics tell us something about the quality of the dataset?* We can assume (just looking at the results) that they do. A dataset with bad quality could be considered one that has high overlapping, imbalanced classes, etc. As the results seem to indicate a relation between those values and the performance of the obtained classifier - as the analytical metrics tell us. This should tell us that we need to explore ways to improve the data (feature engineering, collect further attributes, etc.).

Table 3.10: All Metrics

Measure	Metr.	ant	apache	camel	ivy	jeudi	log4j
Balance	C1	0.7653	0.9805	0.7114	0.5108	0.1545	0.3953
	C2	0.4701	0.0286	0.1227	0.7477	0.9543	0.8319
	C3	0.2622	0.0891	0.1227	0.1879	0.0448	0.0804
	C4	0.6338	0.7372	0.5763	0.5588	0.5324	0.5780
Correlation	T2	0.7409	1.0000	1.0000	0.3722	0.0285	0.4341
	T3	0.0268	0.0524	0.0207	0.0568	0.0407	0.0976
	T4	0.0027	0.0105	0.3000	0.0057	0.0020	0.0098
	T5	0.2477	0.3937	0.2774	0.1570	0.0475	0.1426
Linearity	L2	0.1212	0.1917	0.1370	0.0726	0.0200	0.0624
	L3	0.1103	0.1828	0.1304	0.0661	0.0180	0.0593
	N1	0.3208	0.3822	0.3565	0.2159	0.0447	0.2195
	N2	0.3588	0.3232	0.3629	0.3285	0.2543	0.3588
Neighbor.	N3	0.2067	0.1937	0.2435	0.1364	0.0325	0.1220
	N4	0.0913	0.1728	0.1358	0.0739	0.0122	0.0293
	T1	0.0025	0.0135	0.0021	0.0082	0.0184	0.0161
	L5C	0.9860	0.9659	0.9923	0.9533	0.8870	0.9476
Network	Density	0.8658	0.8801	0.8627	0.8293	0.8170	0.8260
	CisCoef	0.3377	0.2232	0.3131	0.3564	0.3314	0.4158
	Hubs	0.7665	0.9236	0.7608	0.7628	0.8789	0.8487
	F1	0.9192	0.9776	0.9825	0.9432	0.9874	0.9922
Overlap	F1v	0.2882	0.4659	0.5203	0.2083	0.2048	0.3223
	F2	0.0000	0.0061	0.0004	0.0005	0.0000	0.0000
	F3	0.9074	0.9476	0.9513	0.7102	0.5915	0.6585
	F4	0.8295	0.8325	0.8487	0.3977	0.0671	0.1659
Smooth.	S1	0.2191	0.2474	0.2541	0.1453	0.0285	0.1520
	S2	0.1410	0.1178	0.1389	0.1460	0.1417	0.1556
	S3	0.2067	0.1937	0.2466	0.1364	0.0325	0.1220
	S4	0.0847	0.1273	0.1608	0.0716	0.0215	0.0285
Precision	1	0.5600	0.4598	0.6263	0.4976	0.3401	0.9350
	2	0.5093	0.3699	0.6367	0.4674	0.3451	0.9630
	3	0.5152	0.4200	0.6166	0.4633	0.3422	0.9665
	4	0.5497	0.4677	0.5105	0.4198	0.3432	0.9734
Recall	1	0.6068	0.6416	0.4788	0.3167	0.5000	0.4912
	2	0.5913	0.5115	0.5164	0.3744	0.3122	0.4786
	3	0.1231	0.1552	0.0866	0.1987	0.1008	0.9151
	4	0.1703	0.3126	0.0790	0.2722	0.1008	0.5498
Fall Out	1	0.1609	0.2051	0.0919	0.2079	0.0226	0.9261
	2	0.7133	0.6563	0.7120	0.5485	0.0226	0.7333
	3	0.7182	0.6645	0.6998	0.6372	0.0226	0.4000
	4	0.7152	0.6532	0.7122	0.5518	0.0226	0.3533
Balanced	1	0.5547	0.4598	0.5610	0.4268	0.6097	0.4608
	2	0.5445	0.4672	0.5423	0.3646	0.6097	0.4635
	3	0.5489	0.4606	0.5605	0.3801	0.6097	0.4635
	4	0.4295	0.3096	0.4577	0.4799	0.6097	0.4608
FI	1	0.4117	0.2809	0.4446	0.4522	0.6097	0.4635
	2	0.4114	0.2872	0.4538	0.4554	0.6097	0.4635
	3	0.4114	0.2872	0.4538	0.4554	0.6097	0.4635
	4	0.4114	0.2872	0.4538	0.4554	0.6097	0.4635
MCC	1	0.7133	0.6563	0.7120	0.5485	0.0226	0.4000
	2	0.7182	0.6645	0.6998	0.6372	0.0226	0.3533
	3	0.7152	0.6532	0.7122	0.5518	0.0226	0.4000
	4	0.7133	0.6563	0.7120	0.5485	0.0226	0.3533
AUC	1	0.7133	0.6563	0.7120	0.5485	0.0226	0.4000
	2	0.7182	0.6645	0.6998	0.6372	0.0226	0.3533
	3	0.7152	0.6532	0.7122	0.5518	0.0226	0.4000
	4	0.7133	0.6563	0.7120	0.5485	0.0226	0.3533

Table 3.1.1: All Metrics

Measure	Metric	synapse			zelen			sacres			hadoop 0.1			hadoop 0.2			hadoop 0.3		
		NB	DT	NC	NB	DT	NC	NB	DT	NC	NB	DT	NC	NB	DT	NC	NB	DT	NC
Balance	C1	0.6317	0.5581	0.6431	0.9963	0.9944	0.9971	0.9339	0.9374	0.9283	0.6933	0.4782	0.5091	0.1357	0.0286	0.1097	0.6467	0.3671	0.5821
	C2	0.5499	0.4756	0.6472	0.9942	0.9973	1.0000	0.9200	0.9395	0.9385	0.6515	0.5028	0.5933	0.1335	0.1998	0.1852	0.6384	0.3965	0.6784
	C3	0.6325	0.5645	0.6444	0.9952	0.9955	0.9971	0.9322	0.9347	0.9283	0.6933	0.5246	0.5091	0.1324	0.1059	0.1403	0.6133	0.3666	0.5738
Correlation	C4	0.4927	0.5641	0.4950	0.8721	0.9911	0.9330	0.5768	0.9250	0.3007	0.3086	0.6962	0.3276	0.1736	0.1000	0.3305	0.7038	0.8410	0.7295
	T2	0.5353	0.5741	0.5309	0.9511	0.7158	0.4923	0.6346	0.8836	0.2577	0.4814	0.6905	0.4447	0.2634	0.3915	0.4613	0.5322	0.8189	0.4900
	S	0.5618	0.6636	0.5342	0.9032	0.9933	0.4019	0.5931	0.9218	0.3007	0.3276	0.7795	0.3276	0.1638	0.3276	0.3442	0.7133	0.8457	0.7391
Fall Out	1	0.1613	0.2309	0.1467	0.2167	0.3667	0.0500	0.1200	0.1832	0.0669	0.0835	0.3650	0.1437	0.2528	0.3141	0.5494	0.0464	0.1936	0.0820
	2	0.2225	0.3016	0.1399	0.3867	0.0800	0.0000	0.1576	0.1607	0.0498	0.1468	0.3306	0.1628	0.3558	0.4480	0.5418	0.0996	0.4086	0.1129
	3	0.1767	0.2634	0.1579	0.3167	0.2667	0.0500	0.1271	0.1880	0.0669	0.0835	0.3553	0.1437	0.5278	0.3680	0.5611	0.0566	0.1841	0.0872
Balanced	1	0.6657	0.6666	0.6742	0.8277	0.8122	0.6715	0.7284	0.8710	0.6169	0.6126	0.6656	0.5920	0.4604	0.7739	0.3906	0.7739	0.7642	0.7619
	2	0.6564	0.6362	0.6955	0.7822	0.8179	0.7461	0.7385	0.8614	0.6039	0.6673	0.6699	0.6410	0.4538	0.4717	0.4598	0.7163	0.7051	0.6885
	3	0.6926	0.7001	0.6881	0.7933	0.8633	0.6759	0.7330	0.8669	0.6169	0.6221	0.7121	0.5920	0.3597	0.3979	0.3916	0.7784	0.7737	0.7688
F1	1	0.5450	0.5495	0.5506	0.9295	0.9927	0.5623	0.7126	0.9311	0.4534	0.4071	0.5033	0.3942	0.0702	0.0444	0.0969	0.6307	0.3834	0.5626
	2	0.5286	0.5124	0.5754	0.9717	0.8268	0.6487	0.7500	0.9103	0.3993	0.5389	0.5776	0.5015	0.1642	0.2637	0.2389	0.5738	0.5184	0.5567
	3	0.5823	0.5955	0.5721	0.9467	0.9944	0.5712	0.7244	0.9282	0.4534	0.4235	0.5523	0.3942	0.0805	0.0812	0.1134	0.6092	0.3915	0.5657
MCC	1	0.3601	0.3322	0.3780	0.1999	0.4730	0.0693	0.3998	0.7314	0.2375	0.2969	0.2480	0.2093	-0.0751	-0.1679	-0.1940	0.4862	0.2945	0.4438
	2	0.3131	0.2548	0.4089	0.3450	0.1551	0.0962	0.4167	0.6855	0.2254	0.3677	0.3349	0.3051	-0.0992	-0.0367	-0.0672	0.4569	0.3571	0.4334
	3	0.3971	0.3855	0.3983	0.1871	0.6163	0.0708	0.4073	0.7251	0.2375	0.3108	0.3369	0.2093	-0.2479	-0.1659	-0.1773	0.4592	0.2994	0.4363
AUC	1	0.6657	0.6666	0.6742	0.8277	0.8122	0.6715	0.7284	0.8710	0.6169	0.6126	0.6656	0.5920	0.4604	0.3929	0.3906	0.8543*	0.8540*	0.8571*
	2	0.6564	0.6362	0.6955	0.7822	0.8179	0.7461	0.7385	0.8614	0.6039	0.6673	0.6699	0.6410	0.4538	0.4717	0.4598	0.7163	0.7051	0.6885
	3	0.6926	0.7001	0.6881	0.7933	0.8633	0.6759	0.7330	0.8669	0.6169	0.6221	0.7121	0.5920	0.3597	0.3979	0.3916	0.8480*	0.8599*	0.8538*

Table 3.12: All Metrics

Measure	Metric	hadoop 0.4				hadoop 0.5				hadoop 0.6				hadoop 0.7				hadoop 0.8			
Balance	C1	0.7395	0.4632	0.3438	0.3619	0.1294	0.2726	0.3700	0.1600	0.0000	0.3149	0.3302	0.2639	0.2667	0.0719	0.1130	0.0384	0.3534	0.8579	0.1241	0.4917
	C2	0.5062	0.2003	0.3316	0.2332	0.1710	0.2274	0.3267	0.2323	0.5909	0.3433	0.2340	0.3688	0.0719	0.1130	0.0384	0.3534	0.8579	0.1241	0.4917	0.2125
	C3	0.5056	0.3571	0.3395	0.2267	0.1775	0.2155	0.1567	0.2318	0.0000	0.3067	0.2968	0.2693	0.0569	0.1000	0.0417	0.0143	0.0292	0.0042	0.1134	0.0550
Correlation	C4	1.0000	0.4868	0.3240	0.2174	0.1687	0.3062	0.2192	0.0500	0.0000	0.2554	0.5484	0.3218	0.0750	0.0000	0.6000	0.6000	0.2667	0.5000	0.6000	0.2667
	T2	0.0348	0.4451	0.3321	0.2713	0.5327	0.2982	0.5695	0.7195	0.4889	0.3500	0.5833	0.3643	0.2667	0.5000	0.6000	0.2667	0.5000	0.6000	0.2667	0.5000
	T3	0.0050	0.4344	0.3565	0.3164	0.2228	0.3723	0.2067	0.1525	0.0000	0.2954	0.5537	0.4270	0.3500	0.0750	0.6000	0.2667	0.5000	0.6000	0.2667	0.5000
Dimensional	L1	0.2950	0.1498	0.1637	0.2145	0.4981	0.1926	0.1765	0.3742	0.0792	0.1585	0.4321	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045	0.0474
	L2	0.1473	0.1915	0.1757	0.1387	0.2685	0.3335	0.0820	0.1207	0.0000	0.1181	0.2058	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
	L3	0.1408	0.1915	0.1757	0.1387	0.2685	0.3335	0.0820	0.1207	0.0000	0.1181	0.2058	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
Linearity	N1	0.4378	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
	N2	0.4207	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
	N3	0.3234	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
Neighborh.	N4	0.1990	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
	T1	0.0101	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
	LSC	0.9708	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
Network	Density	0.8433	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
	ClsCoef	0.4453	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
	Hubs	0.9121	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
Overlap	F1	0.9641	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
	F1v	0.5797	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
	F2	0.1107	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
Smooth.	F3	0.9900	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
	F4	0.9453	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
	S1	0.3100	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
Precision	S2	0.1075	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
	S3	0.3284	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
	S4	0.1516	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
Recall	1	0.4150	0.4632	0.3438	0.3619	0.1294	0.2726	0.3700	0.1600	0.0000	0.3149	0.3302	0.2639	0.2667	0.0719	0.1130	0.0384	0.3534	0.8579	0.1241	0.4917
	2	0.4267	0.2003	0.3316	0.2332	0.1710	0.2274	0.3267	0.2323	0.5909	0.3433	0.2340	0.3688	0.0719	0.1130	0.0384	0.3534	0.8579	0.1241	0.4917	0.2125
	3	0.3778	0.3571	0.3395	0.2267	0.1775	0.2155	0.1567	0.2318	0.0000	0.3067	0.2968	0.2693	0.0569	0.1000	0.0417	0.0143	0.0292	0.0042	0.1134	0.0550
Full Out	1	0.2478	0.4868	0.3240	0.2174	0.1687	0.3062	0.2192	0.0500	0.0000	0.2554	0.5484	0.3218	0.0750	0.0000	0.6000	0.6000	0.2667	0.5000	0.6000	0.2667
	2	0.4165	0.4451	0.3321	0.2713	0.5327	0.2982	0.5695	0.7195	0.4889	0.3500	0.5833	0.3643	0.2667	0.5000	0.6000	0.2667	0.5000	0.6000	0.2667	0.5000
	3	0.3164	0.4344	0.3565	0.3164	0.2228	0.3723	0.2067	0.1525	0.0000	0.2954	0.5537	0.4270	0.3500	0.0750	0.6000	0.2667	0.5000	0.6000	0.2667	0.5000
Balanced	1	0.0990	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
	2	0.1498	0.1244	0.1629	0.0885	0.2025	0.1959	0.0683	0.0524	0.0000	0.0928	0.1716	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
	3	0.1522	0.1915	0.1757	0.1387	0.2685	0.3335	0.0820	0.1207	0.0000	0.1181	0.2058	0.1774	0.1740	0.2203	0.2902	0.4134	0.6045	0.0474	0.0272	0.6045
F1	1	0.5744	0.6812	0.5805	0.5645	0.4831	0.5551	0.5754	0.4988	0.5000	0.6753	0.7644	0.6602	0.5138	0.4864	0.4977	0.0000	0.4977	0.0000	0.4977	0.0000
	2	0.6334	0.4777	0.5842	0.5284	0.5173	0.5528	0.6965	0.6726	0.7048	0.5958	0.5756	0.5951	0.5232	0.6049	0.4266	0.0000	0.4266	0.0000	0.4266	0.0000
	3	0.5821	0.6214	0.5904	0.5227	0.4772	0.5194	0.5623	0.5159	0.5000	0.6827	0.7519	0.7021	0.5356	0.4635	0.5000	0.0000	0.4635	0.0000	0.4635	0.0000
MCC	1	0.2896	0.4405	0.3090	0.2507	0.1397	0.2680	0.1813	0.0762	0.0000	0.2347	0.2974	0.2314	0.1016	0.0000	0.0735	0.0000	0.0735	0.0000	0.0735	0.0000
	2	0.3952	0.2738	0.3268	0.2268	0.2554	0.2453	0.4051	0.3372	0.4850	0.3403	0.3224	0.3525	0.1111	0.1785	0.0644	0.0000	0.0644	0.0000	0.0644	0.0000
	3	0.3165	0.3699	0.3324	0.1834	0.1789	0.2679	0.1486	0.0750	0.0000	0.2524	0.2784	0.2502	0.0919	0.0833	0.0735	0.0000	0.0735	0.0000	0.0735	0.0000
AUC	1	0.1832	0.3324	0.1645	0.1589	-0.0435	0.1108	0.1595	0.0220	0.0000	0.1572	0.2647	0.1267	0.0932	-0.0347	-0.0088	0.0000	-0.0088	0.0000	-0.0088	0.0000
	2	0.2686	-0.0322	0.1628	0.0600	0.0153	0.0882	0.3136	0.2382	0.4386	0.1930	0.1153	0.2090	0.0182	0.1147	-0.0751	0.0000	-0.0751	0.0000	-0.0751	0.0000
	3	0.1767	0.2116	0.1781	0.0489	-0.0172	0.0347	0.1053	0.0395	0.0000	0.1599	0.2277	0.1595	0.0078	0.0055	0.0000	0.0000	0.0055	0.0000	0.0055	0.0000
	1	0.5744	0.6812	0.5805	0.5645	0.4831	0.5551	0.5754	0.4988	0.5000	0.6753	0.7644	0.6602	0.5138	0.4864	0.4977	0.0000	0.4977	0.0000	0.4977	0.0000
	2	0.6334	0.4777	0.5842	0.5284	0.5173	0.5528	0.6965	0.6726	0.7048	0.5958	0.5756	0.5951	0.5232	0.6049	0.4266	0.0000	0.4266	0.0000	0.4266	0.0000
	3	0.5821	0.6214	0.5904	0.5227	0.4772	0.5194	0.5623	0.5159	0.5000	0.6827	0.7519	0.7021	0.5356	0.4635	0.5000	0.0000	0.4635	0.0000	0.4635	0.0000

Chapter 4

Conclusions and Future Work

4.1. Conclusions

In this work, we analysed data complexity metrics, as well as analytical metrics obtained from the confusion matrix and some basic classifiers. To recapitulate, the following work was conducted through this dissertation:

1. An introduction to *data complexity metrics*, class imbalance and techniques to mitigate its effects, datasets used for the experimentation, and analytical metrics (see Chapter 2, Sections 3.1 and 3.3).
2. Python implementation of the experimentation (connecting to R's `ECol` to obtain the complexity metrics) - see Section 3.4:
 - Obtain the complexity metrics of the datasets.
 - Calculate the analytical metrics of the datasets using K-fold.
 - Compute the analytical metrics of the datasets after applying Under/Oversampling to each fold.
3. Analysis of the obtained results (see Section 3.4.5).

The experiments carried out showed that the datasets selected have many *problems* including *imbalanced classes*, and data *overlapping* are some of them. This could be one of the reasons why the classifiers do not achieve the expected results.

It has also been tried out a few way to improve the classification in those datasets, such as K-folding Cross Validation combined with Undersampling and Oversampling techniques. The result of those experiments led to the intuition that either the applied techniques are not fit for the datasets (do not manage to increase the performance); or that the classification algorithms selected do not perform as well as they were expected. To solve this, in addition to further research, better datasets should be generated, trying to reduce the value of metrics such as overlapping, and therefore maximize linearity; reduce the class imbalance, etc. We also need to explore other balancing techniques than the ones used for this paper.

It could also happen that the number of minority class samples are not only low, but that some folds might not get enough samples of that class - could be solved by increasing the number of samples collected for a certain dataset, or redistributing the minority class through the folds. This would also explain why imbalance techniques are not able to improve the performance of the classifiers

In summary, we observed that the nature of the data might affect the results and this needs further explored in several path as stated next.

4.2. Future Work

There are several paths that can follow this work. First we need to run all experiments with more datasets - trying to have a wider variety of the values obtained in the complexity metrics - and classification algorithms, that could lead to better results than the ones used. Other way would be to apply other imbalance techniques could be applied to the datasets.

The final objective is to try minimize/maximize the aforementioned complexity metrics, which should lead to better classification results.

There are also other paths to follow, for example, analyze the data/quality in the context of feature selection. There is also another path to to do so with interpretable machine learning [\[56\]](#).

Bibliography

- [1] I. Corporation, “Removing unfair bias in machine learning,” pp. 1–27, 2019.
- [2] A. C. Lorena, L. P. Garcia, J. Lehmann, M. C. Souto, and T. K. Ho, “How complex is your classification problem?: A survey on measuring classification complexity,” *ACM Computing Surveys*, vol. 52, no. 5, aug 2019. [Online]. Available: <https://arxiv.org/abs/1808.03591>
- [3] A. Lorena, A. Maciel, P. Miranda, I. Costa, and R. Prudêncio, “Data complexity meta-features for regression problems,” *Machine Learning*, 12 2017.
- [4] T. K. Ho and M. Basu, “Complexity measures of supervised classification problems,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 3, pp. 289–300, March 2002.
- [5] A. C. Lorena, L. P. F. Garcia, J. Lehmann, M. C. P. Souto, and T. K. Ho, “How complex is your classification problem? a survey on measuring classification complexity,” 2018.
- [6] M. Basu and T. K. Ho, Eds., *Data Complexity in Pattern Recognition*. Springer London, 2006. [Online]. Available: <https://doi.org/10.1007/978-1-84628-172-3>
- [7] J. Friedman and L. Rafsky, “Multivariate generalizations of the wald-wolfowitz and smirnov two-sample tests,” *The Annals of Statistics*, vol. 7, no. 4, pp. 697–717, 1979.
- [8] F. Smith, “Pattern classifier design by linear programming,” *IEEE Trans. Computers*, vol. 17, no. 4, pp. 367–372.
- [9] J. Zhang and I. Mani, “Knn approach to unbalanced data distributions: A case study involving information extraction,” 2003. [Online]. Available: <https://www.site.uottawa.ca/~nat/Workshop2003/jzhang.pdf>
- [10] D. Wilson, “Asymptotic properties of nearest neighbor rules using edited data,” *IEEE Transactions on Systems, Man and Cybernetics*, no. 3, pp. 408–421, 1972.
- [11] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, “Smote: Synthetic minority over-sampling technique,” *J. Artif. Intell. Res. (JAIR)*, vol. 16, pp. 321–357, 2002.
- [12] L. Breiman, “Bagging predictors,” *Machine Learning*, vol. 24, pp. 123–140, 1996. [Online]. Available: <http://dx.doi.org/10.1007/BF00058655>
- [13] Y. Freund and R. E. Schapire, “Experiments with a new boosting algorithm,” in *Thirteenth International Conference on Machine Learning*. San Francisco: Morgan Kaufmann, 1996, pp. 148–156.
- [14] N. Chawla, K. Bowyer, L. Hall, and W. Kegelmeyer, “Smote: Synthetic minority over-sampling technique,” *Journal of Artificial Intelligence Research*, vol. 16, pp. 321–357, 2002.

-
- [15] N. Chawla, A. Lazarevic, L. Hall, and K. Bowyer, "Smoteboost: Improving prediction of the minority class in boosting," in *7th European Conference on Principles and Practice of Knowledge Discovery in Databases(PKDD 2003)*, 2003, pp. 107–119.
 - [16] Y. Freund and R. Schapire, "A decision-theoretic generalization of on-line learning and an application to boosting," *Journal of Computer and System Sciences*, vol. 55, no. 1, pp. 119–139, 1997.
 - [17] C. Seiffert, T. Khoshgoftaar, J. Van Hulse, and A. Napolitano, "RUSBoost: A hybrid approach to alleviating class imbalance," *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, vol. 40, no. 1, pp. 185–197, 2010.
 - [18] P. Domingos, "Metacost: a general method for making classifiers cost-sensitive," in *Proceedings of the fifth ACM SIGKDD international conference on Knowledge discovery and data mining*, ser. KDD '99. New York, NY, USA: ACM, 1999, pp. 155–164. [Online]. Available: <http://doi.acm.org/10.1145/312129.312220>
 - [19] S. Bibi, G. Tsoumakas, I. Stamelos, and I. Vlahavas, "Regression via classification applied on software defect estimation," *Expert Systems with Applications*, vol. 34, no. 3, pp. 2091–2101, Apr. 2008. [Online]. Available: <https://doi.org/10.1016/j.eswa.2007.02.012>
 - [20] K. O. Elish and M. O. Elish, "Predicting defect-prone software modules using support vector machines," *Journal of Systems and Software*, vol. 81, no. 5, pp. 649–660, 2008. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S016412120700235X>
 - [21] T. M. Khoshgoftaar, E. Allen, and J. Deng, "Using regression trees to classify fault-prone software modules," *IEEE Transactions on Reliability*, vol. 51, no. 4, pp. 455–462, 2002.
 - [22] T. M. Khoshgoftaar, E. Allen, J. Hudepohl, and S. Aud, "Application of neural networks to software quality modeling of a very large telecommunications system," *IEEE Transactions on Neural Networks*, vol. 8, no. 4, pp. 902–909, 1997.
 - [23] T. Menzies, A. Dekhtyar, J. Distefano, and J. Greenwald, "Problems with precision: A response to comments on data mining static code attributes to learn defect predictors," *IEEE Transactions on Software Engineering*, vol. 33, no. 9, pp. 637–640, 2007.
 - [24] O. Vandecruys, D. Martens, B. Baesens, C. Mues, M. De Backer, and R. Haesen, "Mining software repositories for comprehensible software fault prediction models," *Journal of Systems and Software*, vol. 81, no. 5, pp. 823–839, 2008. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0164121207001902>
 - [25] T. Mende and R. Koschke, "Revisiting the evaluation of defect prediction models," in *Proceedings of the 5th International Conference on Predictor Models in Software Engineering (PROMISE'09)*. New York, NY, USA: ACM, 2009, pp. 1–10.
 - [26] H. Zhang and X. Zhang, "Comments on "data mining static code attributes to learn defect predictors"," *IEEE Transactions on Software Engineering*, vol. 33, no. 9, pp. 635–637, 2007.
 - [27] C. Seiffert, T. Khoshgoftaar, and J. Van Hulse, "Improving software-quality predictions with data sampling and boosting," *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on*, vol. 39, no. 6, pp. 1283–1294, 2009.
 - [28] T. M. Khoshgoftaar and N. Seliya, "Analogy-based practical classification rules for software quality estimation," *Empirical Software Engineering*, vol. 8, no. 4, pp. 325–350, 2003.

-
- [29] Y. Peng, G. Kou, G. Wang, H. Wang, and F. Ko, "Empirical evaluation of classifiers for software risk management," *International Journal of Information Technology & Decision Making (IJITDM)*, vol. 08, no. 04, pp. 749–767, 2009.
 - [30] Y. Peng, G. Wang, and H. Wang, "User preferences based software defect detection algorithms selection using MCDM," *Information Sciences*, vol. In Press., pp. –, 2010. [Online]. Available: <http://www.sciencedirect.com/science/article/B6V0C-4YXK4KM-1/2/0841843c022cfd6b78886eb45bc8ccf0>
 - [31] S. Lessmann, B. Baesens, C. Mues, and S. Pietsch, "Benchmarking classification models for software defect prediction: A proposed framework and novel findings," *IEEE Transactions on Software Engineering*, vol. 34, no. 4, pp. 485–496, July-Aug. 2008.
 - [32] T. Mende and R. Koschke, "Effort-aware defect prediction models," in *Proceedings of the 2010 14th European Conference on Software Maintenance and Reengineering (CSMR'10)*, ser. CSMR'10. Washington, DC, USA: IEEE Computer Society, 2010, pp. 107–116. [Online]. Available: <http://dx.doi.org/10.1109/CSMR.2010.18>
 - [33] M. Jureczko and L. Madeyski, "Towards identifying software project clusters with regard to defect prediction," in *Proceedings of the 6th International Conference on Predictive Models in Software Engineering - PROMISE'10*. ACM Press, 2010.
 - [34] L. Madeyski and J. Hrysko, "Bottlenecks in software defect prediction implementation in industrial projects," vol. 40, no. 1, 2015.
 - [35] T. Zimmermann, R. Premraj, and A. Zeller, "Predicting defects for eclipse," in *International Workshop on Predictor Models in Software Engineering (PROMISE'07)*, may 2007, p. 9.
 - [36] M. Harman, S. Islam, Y. Jia, L. L. Minku, F. Sarro, and K. Srivisut, "Less is more: Temporal fault predictive performance over multiple hadoop releases," in *Search-Based Software Engineering*, C. Le Goues and S. Yoo, Eds. Cham: Springer International Publishing, 2014, pp. 240–246.
 - [37] "The promise repository of empirical software engineering data," 2015.
 - [38] Z. Xu, J. Liu, X. Luo, and T. Zhang, "Cross-version defect prediction via hybrid active learning with kernel principal component analysis," in *2018 IEEE 25th International Conference on Software Analysis, Evolution and Reengineering (SANER)*. IEEE, mar 2018.
 - [39] S. Wang, T. Liu, and L. Tan, "Automatically learning semantic features for defect prediction," in *Proceedings of the 38th International Conference on Software Engineering - ICSE'16*. ACM Press, 2016.
 - [40] X. Xia, D. Lo, S. J. Pan, N. Nagappan, and X. Wang, "HYDRA: Massively compositional model for cross-project defect prediction," *IEEE Transactions on Software Engineering*, vol. 42, no. 10, pp. 977–998, oct 2016.
 - [41] S. Chidamber and C. Kemerer, "A metrics suite for object oriented design," *IEEE Transactions on Software Engineering*, vol. 20, no. 6, pp. 476–493, jun 1994.
 - [42] R. Martin, "OO Design Quality Metrics - An Analysis of Dependencies," in *Proceedings Workshop Pragmatic and Theoretical Directions in Object-Oriented Software Metrics*, 1994, pp. 151–170.
 - [43] J. Bansiya and C. Davis, "A hierarchical model for object-oriented design quality assessment," *IEEE Transactions on Software Engineering*, vol. 28, no. 1, pp. 4–17, 2002.

- [44] Henderson-Sellers, *Object-Oriented Metrics: Measures of Complexity*. ADDISON WESLEY PUB CO INC, 1995. [Online]. Available: https://www.ebook.de/de/product/6141164/henderson_sellers_object_oriented_metrics_measures_of_complexity.html
- [45] M.-H. Tang, M.-H. Kao, and M.-H. Chen, "An empirical study on object-oriented metrics," in *Proceedings Sixth International Software Metrics Symposium (Cat. No.PR00403)*. IEEE Comput. Soc.
- [46] T. McCabe, "A complexity measure," *IEEE Transactions on Software Engineering*, vol. SE-2, no. 4, pp. 308–320, dec 1976.
- [47] T. Mitchell, *Machine Learning*. McGraw Hill, 1997.
- [48] L. Breiman, J. H. Friedman, R. A. Olshen, and C. J. Stone, *Classification and Regression Trees*. Belmont, California: Wadsworth International Group, 1984, https://books.google.es/books/about/Classification_and_Regression_Trees.html?id=JwQx-WOmSyQC&redir_esc=y.
- [49] J. Quinlan, *C4.5: Programs for machine learning*. San Mateo, California: Morgan Kaufmann, 1993.
- [50] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.
- [51] "Conformal prediction for reliable machine learning," in *Conformal Prediction for Reliable Machine Learning*, V. N. Balasubramanian, S.-S. Ho, and V. Vovk, Eds. Boston: Morgan Kaufmann, 2014, p. i. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/B9780123985378000146>
- [52] T. Sørensen, "A method of establishing groups of equal amplitude in plant sociology based on similarity of species and its application to analyses of the vegetation on danish commons," vol. 5(4), pp. 1–34, 1948.
- [53] L. R. Dice, "Measures of the amount of ecologic association between species," *Ecology*, vol. 26(3), pp. 297–302, 1945.
- [54] B. Matthews, "Comparison of the predicted and observed secondary structure of t4 phage lysozyme," *Biochimica et Biophysica Acta (BBA) - Protein Structure*, vol. 405, no. 2, pp. 442–451, Oct. 1975. [Online]. Available: [https://doi.org/10.1016/0005-2795\(75\)90109-9](https://doi.org/10.1016/0005-2795(75)90109-9)
- [55] T. Fawcett, "An introduction to ROC analysis," *Pattern Recognition Letters*, vol. 27, no. 8, pp. 861–874, Jun. 2006. [Online]. Available: <https://doi.org/10.1016/j.patrec.2005.10.010>
- [56] C. Molnar, *Interpretable Machine Learning*, 2019, <https://christophm.github.io/interpretable-ml-book/>.

Appendix A

Prerequisites

Some relevant code sections have been included. The whole project is publicly available on GitHub: <https://github.com/PabloAceG/ComputingProject>.

To be able to execute the experiments within the repository, Python3 is needed. Anaconda or the official Python located in the official repositories can be used as long as version 3 or posterior is used. Trying to replicate the experiments on some operative systems might terminate in error. If this is the case, python can be changed (*Linux*) with:

```
1 sudo update-alternatives --config python
```

R (programming language) is needed before trying to execute the project. Also, the following packages are mandatory in order to replicate the experiments:

- ECoL - Dataset Complexity Metrics Package.
 - <https://github.com/lpfgarcia/ECoL>
 - <https://cran.r-project.org/web/packages/ECoL/>
- Rserve - server, responds requests made to R: <https://rforge.net/Rserve/doc.html>.

Once the previous requisites are fulfilled, the R server can be started by executing the following commands:

```
1 library(Rserve) # import the library
2 run.Rserve() # start the server. Or simply Rserve()
```

Now, it is time to download the project to install the remaining Python packages. The project can be downloaded from <https://github.com/PabloAceG/ComputingProject/>.

Same as before, some Python packages are mandatory to execute the project. These packages are available in requirements.txt ¹ file. To automatically install those packages, run²:

```
1 pip install -r .\code\requirements.txt
```

It might happen that pip install -r might not install all packages. To solve this, the failing packages must be installed manually:

```
1 pip install <package_name>
```

¹<https://github.com/PabloAceG/ComputingProject/blob/master/code/requirements.txt>

²All commands are executed from the parent folder of the repository.

Now, the experiments should be replicable. The experiment's code is under the folder <https://github.com/PabloAceG/ComputingProject/tree/master/code> To run them, execute:

```
1 python code/metrics_comparison.py
2 python code/metrics_kfold.py
3 python code/metrics_kfold_undersampling.py
4 python code/metrics_kfold_oversampling.py
```

Each of the previous commands execute one experiment.

As final remarks, the class `r_connect.py`³ is the client connection the server in R (Rserve). It makes the requests to the `ECOL` package to obtain the complexity metrics.

The class `data.py`⁴ standardizes the datasets input (parsing data) and some other metrics from the package `sklearn`⁵.

³https://github.com/PabloAceG/ComputingProject/blob/master/code/r_connect.py

⁴<https://github.com/PabloAceG/ComputingProject/blob/master/code/data.py>

⁵<https://scikit-learn.org/stable/index.html>

Appendix B

Python Relevant Code

B.1. Rserve Python Client

The class `r_connect.py` is a client for R package Rserve. Makes requests to ECoL R package and parses data.

The import statements have been made redundant in this snippet and the rest of the snippets in this appendix.

```
1 class r_connect:
2
3     __metrics = None
4
5     def __init__ (self):
6         self.__connection = self.__connect ()
7
8     def __connect (self):
9         return pyRserve.connect ()
10
11     def get_metrics (self, X=None, Y=None):
12         if X is None and Y is None :
13             if self.__metrics is not None:
14                 return self.__metrics
15             else :
16                 # No data and no parameters: finish execution
17                 error_message = '...'
18                 raise Exception(error_message)
19                 sys.exit (400)
20         else :
21             # Stores connection to R's RPC.
22             connect = self.__connection
23
24             # Sends the input matrix and the output vector to R.
25             connect.r.X = X
26             connect.r.y = Y
27
28             # Library to use in R.
29             connect.r('df_X <- as.data.frame(X)')
30             connect.r('df_y <- as.data.frame(y)')
31             connect.r('library("ECoL")')
32
33             ## Metrics, uses a dictionary to provide a faster access to its
```

```

34         # contents.
35         metrics = {}
36
37         # Balance: C1, C2
38         balance = self.safe_connect('balance(df_X, df_y)')
39         balance_dic_entry = { 'balance' : balance }
40         metrics.update (balance_dic_entry)
41
42         # Correlation: C1, C2, C3, C4
43         correlation = self.safe_connect('correlation(df_X, df_y, summary=c("mean"))')
44         correlation_dic_entry = { 'correlation' : correlation }
45         metrics.update (correlation_dic_entry)
46
47         # Dimensionality: T2, T3, T4
48         dimensionality = self.safe_connect('dimensionality(df_X, df_y, summary=c("mean"))')
49     )
50     dimensionality_dic_entry = { 'dimensionality' : dimensionality }
51     metrics.update (dimensionality_dic_entry)
52
53     # Linearity: L1, L2, L3
54     linearity = self.safe_connect('linearity(df_X, df_y, summary=c("mean"))')
55     linearity_dic_entry = { 'linearity' : linearity }
56     metrics.update (linearity_dic_entry)
57
58     # Neighborhood: N1, N2, N3, N4, T1, LSC
59     neighborhood = self.safe_connect('neighborhood(df_X, df_y, summary=c("mean"))')
60     neighborhood_dic_entry = { 'neighborhood' : neighborhood }
61     metrics.update (neighborhood_dic_entry)
62
63     # Network: Density, ClsCoef, Hubs
64     network = self.safe_connect('network(df_X, df_y, summary=c("mean"))')
65     network_dic_entry = { 'network' : network }
66     metrics.update (network_dic_entry)
67
68     # Overlap: F1, F1v, F2, F3, F4
69     overlap = self.safe_connect('overlapping(df_X, df_y, summary=c("mean"))')
70     overlap_dic_entry = { 'overlap' : overlap }
71     metrics.update (overlap_dic_entry)
72
73     # Smoothness: S1, S2, S3, S4
74     smoothness = self.safe_connect('smoothness(df_X, df_y, summary=c("mean"))')
75     smoothness_dic_entry = { 'smoothness' : smoothness }
76     metrics.update (smoothness_dic_entry)
77
78     self.__metrics = metrics
79
80     return metrics
81
82     def print_metrics (self, metrics=None) :
83         print ('\\n\\n=== Printing metrics ===', end='\\n\\n')
84
85         ...
86
87     def get_print_metrics(self, X, Y):
88         self.get_metrics (X, Y)
89         self.print_metrics (self.__metrics)
90
91     return self.__metrics

```



```

92
93     def safe_connect(self, operation) :
94         connection = self.__connection
95
96         return connection.r(operation)

```

Listing B.1: Connection code to requests R ECoL functions

B.2. Datasets and Operations on Data

The following code contains the logic to read and parse datasets requested through the function `getDataset(...)`. The datasets can be shuffled if specified through parameter, but in this situation no experiments used that option (as the results should be replicated, the input that should always be the same).

The class also uses *sklearn* library to calculate some metrics. The functions in this code simply parse the results so that they are easier to read afterwards (no need to have more than 4 digits of precision in float numbers).

Not all the code has been copied, as some parts repeat.

```

1  ...
2  ...
3
4  def __load_arff(path):
5      '''
6          Loads the dataset content of an .arff file into the workspace.
7          Input:
8              - path: Location of the file.
9          Output:
10             - dataset: Data from the file.
11      '''
12
13     dataset = []
14
15     with open(path, 'r') as data:
16         dataset = arff.load(data)['data']
17
18     return dataset
19
20 def __load_csv(path):
21     '''
22         Loads the data content of an .csv file into the workspace.
23         Input:
24             - path: Location of the file.
25         Output:
26             - dataset: Data from the file.
27     '''
28
29     dataset = []
30
31     with open(path, 'r') as csv_file:
32         dataset = pd.read_csv(
33             csv_file,
34             sep=',',
35         )
36

```

```

37     return dataset
38
39 def __parte_dataset(dataset, input_select, target_select):
40     '''
41     Takes a dataset and parses it to only take what is necessary.
42     Inputs:
43         - dataset: Input raw data as a Pandas Data Framework.
44         - start: Where columns start to be useful.
45     Output:
46         - input: Input arrays of the dataset.
47         - target: Target column of the dataset.
48     '''
49
50     num_rows = len(dataset)
51     last_column = target_select if (target_select < 0) else None
52
53     # Input
54     input_columns = dataset.columns[input_select:last_column]
55     input = dataset[input_columns].head(num_rows).astype(float).to_numpy()
56
57     # Target
58     target_column = dataset.columns[target_select]
59     target = dataset[target_column].head(num_rows)
60
61     # Parse output
62     sample = target[0]
63     if not isinstance(sample, str):
64         target = numpy.where(target > 0, 1, 0)
65     else:
66         has_faults = target == 'yes'
67         target = numpy.where(has_faults, 1, 0)
68
69     return input, target
70
71 def __data_preparation(path, input_select, target_select, type='arff', shuffle=False):
72     '''
73     Loads an .arff/.csv file and parses its content to input/output valid
74     for a Machine Learning application.
75     Input:
76         - path: Location of the file.
77         - start: Where columns start to be useful (string columns are not
78             necessary).
79         - type: It can be:
80             - arff
81             - csv
82     Output:
83         - input: Input arrays of the dataset.
84         - target: Target column of the dataset.
85     '''
86
87     # Load data
88     dataset = []
89     if type == 'arff':
90         dataset = __load_arff(path)
91     elif type == 'csv':
92         dataset = __load_csv(path)
93     else:
94         raise Exception('Not a valid file type. Try with arff or csv!')
95     sys.exit(404)

```

```

96 dataset = pd.DataFrame(dataset)
97
98 if shuffle:
99     dataset = dataset.sample(frac=1)
100
101 # Parse data
102 data = (dataset, input_select, target_select)
103 input, target = __parte_dataset(*data)
104
105 return input, target
106
107 def __data_preparation_iris_dataset(path):
108     # Load data
109     dataset = __load_csv(path)
110     dataset = pd.DataFrame(dataset)
111
112     # Parse data
113     start = 0
114     last = -1
115     num_rows = len(dataset)
116
117     # Input
118     input_columns = dataset.columns[start : last]
119     input = dataset[input_columns].head(num_rows).astype(float).to_numpy()
120
121     # Target
122     target_column = dataset.columns[last]
123     target = dataset[target_column].head(num_rows)
124
125
126     # Parse target
127     values = {'setosa': 1, 'versicolor': 2, 'virginica': 3}
128     target = numpy.array( [
129         values[type] for type in target
130     ] )
131
132     return input, target
133
134 def get_dataset(name, shuffle=False):
135     '''
136     Retrieves the data of a given dataset, separated into input information
137     and target output - .arff or .csv files only.
138     Input:
139         - name: Dataset name.
140             - ant
141             - apache
142             - camel
143             - iris
144             - ivy
145             - jedit
146             - log4j
147             - poi
148             - synapse
149             - xalan
150             - xerces
151     Output:
152         - input: Input arrays of the dataset.
153         - target: Target column of the dataset.
154     '''

```

```

155
156 path      = ''      # Location of file
157 start      = 0      # From which columns to use
158 output_col = -2     # Position of output column
159 type       = 'arff' # Type of file to be read. Default .arff
160
161 if name == 'ant':
162     # Retrieve data
163     path = './dataset/ant-1.7.arff'
164     start = 3
165
166 elif name == 'apache':
167     # Retrieve data
168     path = './dataset/Apache.csv'
169     start = 3
170     output_col = -1
171     type = 'csv'
172
173 elif name == 'camel':
174     # Retrieve data
175     path = './dataset/camel-1.6.arff'
176     start = 3
177
178 elif name == 'iris': # Special case. Non-binary output. Needs different
179                     # treatment.
180     # Retrieve data
181     path = './dataset/iris.csv'
182     input, target = __data_preparation_iris_dataset(path, shuffle)
183
184     return input, target
185
186 elif name == 'ivy':
187     # Retrieve data
188     path = './dataset/ivy-2.0.arff'
189     start = 3
190
191 ...
192 ...
193 elif name == 'xerces':
194     # Retrieve data
195     path = './dataset/xerces-1.4.arff'
196     start = 3
197
198 elif name == 'hadoop-1':
199     # Retrieve data
200     path = './dataset/hadoop-proc-0.1.csv'
201     start = 2
202     output_col = 1
203     type = 'csv'
204
205 ...
206 ...
207 elif name == 'hadoop-8':
208     # Retrieve data
209     path = './dataset/hadoop-proc-0.8.csv'
210     start = 2
211     output_col = 1
212     type = 'csv'
213

```

```

214
215     else:
216         raise Exception('The given dataset name is not valid.')
217         sys.exit(404)
218
219     # Return results
220     input, target = __data_preparation(path, start, output_col, type, shuffle)
221
222     return input, target
223
224 def confusion_matrix(x_test: list, y_test: list, classifier):
225     '''
226     Obtains the confusion matrix for a given testing dataset, with binary
227     output.
228     Input:
229         - x_test: paremeters for testing dataset.
230         - y_test: target/desired output for testing dataset.
231         - classifier: trained classifier.
232     Output:
233         (
234             true_positive: successfully predicted positives
235             true_negative: successfully predicted negatives
236             false_positive: unsuccessfully predicted positives
237             false_negative: unsuccessfully predicted positives
238         )
239     '''
240     # Confusion Matrix Cells
241     true_positive:float = 0
242     true_negative:float = 0
243     false_positive:float = 0
244     false_negative:float = 0
245
246     # Calculate number of repetitions of each classification.
247     for (input, target) in zip(x_test, y_test):
248         prediction:int = classifier.predict([input])[0]
249
250         if prediction == target:    # Success
251             if prediction: true_positive += 1
252             else:         true_negative += 1
253         else:                      # Wrong
254             if prediction: false_positive += 1
255             else:         false_negative += 1
256
257     # Transform absolute to relative values
258     num_samples = len(y_test)
259     true_positive = true_positive / num_samples
260     true_negative = true_negative / num_samples
261     false_positive = false_positive / num_samples
262     false_negative = false_negative / num_samples
263
264     return (true_positive, true_negative, false_positive, false_negative)
265
266 def recall(targets, predictions) -> float:
267     '''
268     Sensitivity, recall, hit rate or True Positive Rate (RPR)
269     https://scikit-learn.org/stable/modules/generated/sklearn.metrics.recall\_score.html
270         TP      TP
271     TPR = ---- = ----- = 1 - FNR
272         P      TP + FN

```

```

273     '''
274     return round(metrics.recall_score(targets, predictions), 4)
275
276 def fall_out(targets, predictions) -> float:
277     '''
278     Fallout, or False Positive Rate (FPR)
279         FP      FP
280     FPR = ---- = ----- = 1 - TNR
281         N      FP + TN
282     '''
283     # Calculate TN and FP rates
284     num_items:int = len(targets)
285     false_positive:float = 0
286     true_negative: float = 0
287     # Count
288     for (t, o) in zip(targets, predictions):
289         if (o == t and o == 0):
290             true_negative += 1
291         if (o != t and o == 1):
292             false_positive += 1
293     try:
294         # Rates
295         true_negative /= num_items
296         false_positive /= num_items
297
298         # False Positive Rate
299         fdr:float = false_positive / (false_positive + true_negative)
300         return round(fdr, 4)
301     except:
302         return 0
303
304 def precision(targets, predictions) -> float:
305     '''
306     Precision or positive predictive value (PPV).
307     https://scikit-learn.org/stable/modules/generated/sklearn.metrics.precision\_score.html
308         TP
309     PPV = ----- = 1 - FDR
310         TP + FP
311     '''
312     return round(metrics.precision_score(targets, predictions), 4)
313
314 def balanced(targets, predictions) -> float:
315     '''
316     Balanced Accuracy (BA)
317     https://scikit-learn.org/stable/modules/generated/sklearn.metrics.balanced\_accuracy\_score.html#sklearn.metrics.balanced\_accuracy\_score
318         TPR + TNR
319     BA = -----
320         2
321     '''
322
323     return round(metrics.balanced_accuracy_score(targets, predictions), 4)
324
325 def f1(targets, predictions) -> float:
326     '''
327     F1 Score. Is the harmonic mean of precision and sensitivity.
328     https://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1\_score.html
329         PPV x TPR      2 TP
330     F1 = 2 ----- = -----

```

```

331         PPV + TPR      2 TP + FP + FN
332     '''
333     return round(metrics.f1_score(targets, predictions), 4)
334
335 def mcc(targets, predictions) -> float:
336     '''
337         Matthews Correlation Coefficient (MCC).
338         https://scikit-learn.org/stable/modules/generated/sklearn.metrics.matthews_corrcoef.
339         html
340
341         TP x TN - FP x FN
342         MCC = -----
343         sqrt((TP + FP) (TP + FN) (TN + FP) (TN + FN))
344     '''
345     return round(metrics.matthews_corrcoef(targets, predictions), 4)
346
347 def auc(targets, predictions) -> float:
348     '''
349         Area Under Receiver Operating Characteristic Curve,
350         Area Under ROC Curve or AUC.
351         https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html
352         https://scikit-learn.org/stable/modules/generated/sklearn.metrics.auc.html
353         1 + TPR - FPR
354         AUC = -----
355         2
356     '''
357     fpr, tpr, thresholds = metrics.roc_curve(targets, predictions)
358
359     return round(metrics.auc(fpr, tpr), 4)
360
361 def store_results(filename:str, metrics:list):
362     with open('./code/results/' + filename + '.csv', mode='a', newline='') as csvfile:
363         writer = csv.writer(csvfile, delimiter=',', quoting=csv.QUOTE_MINIMAL)
364         writer.writerow(metrics)
365
366 def calculate_results(targets:list, predictions:list) -> list:
367     # Metrics
368     ppv:float = precision(targets, predictions)
369     tpr:float = recall (targets, predictions)
370     fpr:float = fall_out (targets, predictions)
371     ba :float = balanced (targets, predictions)
372     fm :float = f1 (targets, predictions)
373     m :float = mcc (targets, predictions)
374     a :float = auc (targets, predictions)
375     metrics:list = [ppv, tpr, fpr, ba, fm, m, a]
376
377     return metrics
378
379 def train_predict(clf, input_train, target_train, test):
380     # Train
381     clf.fit(input_train, target_train)
382     # Test
383     return clf.predict(test)

```

Listing B.2: Load datasets, calculate metrics, export results to CSV files, etc.


```

50         if cols == 1:
51             if metrics[metric][measure]:
52                 axs[i].bar(datasets, metrics[metric][measure])
53
54             else:
55                 axs[i].text(0.5, 0.5, 'No data')
56
57             title = metric + ': ' + measure
58             axs[i].set_title(title)
59         else:
60             if metrics[metric][measure]:
61                 axs[i, j].bar(datasets, metrics[metric][measure])
62
63             else:
64                 axs[i, j].text(0.5, 0.5, 'No data')
65
66             title = metric + ': ' + measure
67             axs[i, j].set_title(title)
68
69         if j == cols - 1:
70             i += 1
71             j = 0
72         else:
73             j += 1
74
75     i = 0
76     j = 0
77     plt.show()
78
79
80 if __name__ == '__main__':
81     '''
82     Main code - to be executed
83     '''
84
85     # Datasets to analyze
86     '''
87     datasets = [
88         'ant',
89         'apache',
90         'camel',
91         'ivy',
92         'jedit',
93         'log4j',
94         'synapse',
95         'xalan',
96         'xerces'
97     ]
98     '''
99     datasets = [
100         'hadoop-1',
101         'hadoop-2',
102         'hadoop-3',
103         'hadoop-4',
104         'hadoop-5',
105         'hadoop-6',
106         'hadoop-7',
107         'hadoop-8',
108     ]

```

```

109
110
111 # Store metrics computed from datasets (datatype: dict)
112 results = {
113     'balance': {
114         'C1': [],
115         'C2': []
116     },
117     'correlation': {
118         'C1': [],
119         'C2': [],
120         'C3': [],
121         'C4': []
122     },
123     'dimensionality': {
124         'T1': [],
125         'T2': [],
126         'T3': []
127     },
128     'linearity': {
129         'L1': [],
130         'L2': [],
131         'L3': []
132     },
133     'neighborhood': {
134         'N1': [],
135         'N2': [],
136         'N3': [],
137         'N4': [],
138         'T1': [],
139         'LSC': [],
140     },
141     'network': {
142         'Density': [],
143         'ClsCoef': [],
144         'Hubs': []
145     },
146     'overlap': {
147         'F1': [],
148         'F1v': [],
149         'F2': [],
150         'F3': [],
151         'F4': []
152     },
153     'smoothness': {
154         'S1': [],
155         'S2': [],
156         'S3': [],
157         'S4': []
158     }
159 }
160
161 # Connect to R
162 connector = r_connect()
163
164 # Get Metrics
165 for set in datasets:
166     print(set)
167     inputs, targets = DATASETS.get_dataset(set)

```

```

168     metrics = connector.get_metrics(inputs, targets)
169
170     results = add_metrics(results, metrics)
171
172     # Print Metrics
173     print(results)
174     plot_metrics_comparison(results)

```

Listing B.3: Compare complexity metrics of different datasets

B.4. Experiment 2. Compare Metrics on K-fold Cross Validation

The function calls to the *data* (referenced as *DATASETS* in the code) object are unfolded in the snippet B.2.

The objective is to look for a relation between confusion matrix metrics (recall, fallout, etc.) between the folds generated out of a K-fold Cross Validation. See if there is a certain linearity between folds and what might cause certain behaviors.

In order to create this experiment, a dataset is loaded, and then it is folded into k-equally-sized parts. For each part, three different classification algorithms are trained and tested to compare the aforementioned metrics (more about the metrics in 3.3). This same process is repeated for every dataset.

```

1 ...
2 ...
3 import data as DATASETS
4
5 if __name__ == '__main__':
6     # Data
7     datasets = [
8         'ant',
9         'apache',
10        'camel',
11        'ivy',
12        'jedit',
13        'log4j',
14        'poi',
15        'synapse',
16        'xalan',
17        'xerces',
18        'hadoop-1',
19        'hadoop-2',
20        'hadoop-3',
21        'hadoop-4',
22        'hadoop-5',
23        'hadoop-6',
24        'hadoop-7',
25        'hadoop-8'
26    ]
27
28    for d in datasets:
29        print('-----' + d + '-----')
30        inputs, target = DATASETS.get_dataset(d)
31
32        # K-fold Parameters

```

```

33     k = 5
34     kf = KFold(n_splits=k)
35     splits = kf.split(inputs)
36     # Precision Recall Fallout Balanced F1 MCC AUC
37     mean_naive = np.array([0, 0, 0, 0, 0, 0, 0])
38     mean_tree = np.array([0, 0, 0, 0, 0, 0, 0])
39     mean_knn = np.array([0, 0, 0, 0, 0, 0, 0])
40
41     # Get measurements using K-fold
42     for train_index, test_index in splits:
43         # Data partition
44         x_train, x_test = inputs[train_index], inputs[test_index]
45         y_train, y_test = target[train_index], target[test_index]
46
47         filename = d + '-k' + str(k)
48
49         # Train NN
50         print('---> Naive Bayes')
51         clf = GaussianNB()
52         predictions = DATASETS.train_predict(clf, x_train, y_train, x_test)
53         naive_metrics = DATASETS.calculate_results(y_test, predictions)
54         mean_naive = np.add(mean_naive, naive_metrics)
55         naive_metrics = ['Naive Bayes'] + naive_metrics
56         DATASETS.store_results(filename, naive_metrics)
57
58         print('---> Decision Tree')
59         clf = DecisionTreeClassifier()
60         predictions = DATASETS.train_predict(clf, x_train, y_train, x_test)
61         tree_metrics = DATASETS.calculate_results(y_test, predictions)
62         mean_tree = np.add(mean_tree, tree_metrics)
63         tree_metrics = ['Decision Tree'] + tree_metrics
64         DATASETS.store_results(filename, tree_metrics)
65
66         print('---> Nearest Centroid')
67         clf = NearestCentroid()
68         predictions = DATASETS.train_predict(clf, x_train, y_train, x_test)
69         knn_metrics = DATASETS.calculate_results(y_test, predictions)
70         mean_knn = np.add(mean_knn, knn_metrics)
71         knn_metrics = ['Nearest Centroid'] + knn_metrics
72         DATASETS.store_results(filename, knn_metrics)
73
74         print('-----')
75
76     # K-fold Mean
77     mean_naive = [round(i, 4) for i in (mean_naive / k)]
78     DATASETS.store_results(filename, ['Naive Bayes Mean'] + mean_naive)
79     mean_tree = [round(i, 4) for i in (mean_tree / k)]
80     DATASETS.store_results(filename, ['Decision Tree Mean'] + mean_tree)
81     mean_knn = [round(i, 4) for i in (mean_knn / k)]
82     DATASETS.store_results(filename, ['Nearest Centroid Mean'] + mean_knn)
83
84     print([mean_naive, mean_tree, mean_knn])

```

Listing B.4: Calculate Metrics from Confusion Matrix to compare in-fold results

B.5. Experiment 3. Compare Metrics with Under-sampling and K-fold Cross Validation

The function calls to the *data* (referenced as *DATASETS* in the code) object, can be observed in the snippet B.2. Also, the experiment is the same as in B.4, although an under-sampling filter is applied to each fold of the dataset before using any classification algorithm.

This experiment has to be executed as many times as datasets want to be analyzed, as a bulk execution of all the datasets would probably end in error. The reason for this is that if the sampling strategy is too low, then there should not be enough data to properly train the classification. Also, it depends on the amount of samples of the minority class, that is why not a low enough value can be set for all datasets, and a single-dataset execution must be performed.

The values commented at the right of each dataset indicate the recommended sampling strategy for that dataset.

```

1 ...
2 ...
3 import data as DATASETS
4
5 if __name__ == '__main__':
6     # Data
7     # In this case a loop cannot be used to make all experiments, as the value
8     # of the undersampling may vary on each dataset.
9     dataset = 'ant' # 50
10    #dataset = 'apache' # 50
11    #dataset = 'camel' # 50
12    #dataset = 'ivy' # 30
13    #dataset = 'jedit' # 7
14    #dataset = 'log4j' # 11
15    #dataset = 'synapse' # 50
16    #dataset = 'xalan' # 6
17    #dataset = 'xerces' # 50
18    #dataset = 'hadoop-1' # 38
19    #dataset = 'hadoop-2' # 31
20    #dataset = 'hadoop-3' # 35
21    #dataset = 'hadoop-4' # 32
22    #dataset = 'hadoop-5' # 26
23    #dataset = 'hadoop-6' # 22
24    #dataset = 'hadoop-7' # 34
25    #dataset = 'hadoop-8' # 10
26
27    inputs, target = DATASETS.get_dataset(dataset)
28
29    # K-fold Parameters
30    k = 5
31    kf = KFold(n_splits=k, shuffle=True, random_state=1)
32    splits = kf.split(inputs)
33    # Precision Recall Fallout Balanced F1 MCC AUC
34    mean_naive = np.array([0, 0, 0, 0, 0, 0, 0])
35    mean_tree = np.array([0, 0, 0, 0, 0, 0, 0])
36    mean_knn = np.array([0, 0, 0, 0, 0, 0, 0])
37
38    RANDOM_STATE = 42
39
40    # Get measurements using K-fold
41    for train_index, test_index in splits:

```

```

42     # Data partition
43     x_train, x_test = inputs[train_index], inputs[test_index]
44     y_train, y_test = target[train_index], target[test_index]
45
46     X, Y = make_imbalance(
47         x_train, y_train,
48         sampling_strategy={0:50, 1:50},
49         random_state=RANDOM_STATE)
50
51     filename = dataset + '-k' + str(k) + '-under'
52
53     # Train NN
54     print('---> Naive Bayes')
55     clf = GaussianNB()
56     pipeline = make_pipeline(
57         NearMiss(version=2),
58         clf)
59     predictions = DATASETS.train_predict(pipeline, X, Y, x_test)
60     naive_metrics = DATASETS.calculate_results(y_test, predictions)
61     mean_naive = np.add(mean_naive, naive_metrics)
62     naive_metrics = ['Naive Bayes'] + naive_metrics
63     DATASETS.store_results(filename, naive_metrics)
64
65     print('---> Decision Tree')
66     clf = DecisionTreeClassifier()
67     pipeline = make_pipeline(
68         NearMiss(version=2),
69         clf)
70     predictions = DATASETS.train_predict(pipeline, X, Y, x_test)
71     tree_metrics = DATASETS.calculate_results(y_test, predictions)
72     mean_tree = np.add(mean_tree, tree_metrics)
73     tree_metrics = ['Decision Tree'] + tree_metrics
74     DATASETS.store_results(filename, tree_metrics)
75
76     print('---> Nearest Centroid')
77     clf = NearestCentroid()
78     pipeline = make_pipeline(
79         NearMiss(version=2),
80         clf)
81     predictions = DATASETS.train_predict(pipeline, X, Y, x_test)
82     knn_metrics = DATASETS.calculate_results(y_test, predictions)
83     mean_knn = np.add(mean_knn, knn_metrics)
84     knn_metrics = ['Nearest Centroid'] + knn_metrics
85     DATASETS.store_results(filename, knn_metrics)
86
87     print('-----')
88
89     # K-fold Mean
90     mean_naive = [round(i, 4) for i in (mean_naive / k)]
91     DATASETS.store_results(filename, ['Naive Bayes Mean'] + mean_naive)
92     mean_tree = [round(i, 4) for i in (mean_tree / k)]
93     DATASETS.store_results(filename, ['Decision Tree Mean'] + mean_tree)
94     mean_knn = [round(i, 4) for i in (mean_knn / k)]
95     DATASETS.store_results(filename, ['Nearest Centroid Mean'] + mean_knn)
96
97     print([mean_naive, mean_tree, mean_knn])

```

Listing B.5: Calculate Metrics from Confusion Matrix to compare in-fold results after applying under-sampling filter

B.6. Experiment 4. Compare Metrics with Over-sampling and K-fold Cross Validation

The function uses *data* (referenced as *DATASETS* in the code) object - which is unfolded in the snippet B.2. Also, the experiment is the same as in B.4 and B.5, but in this situation an over-sampling filter is applied to each fold of the dataset before starting the classification process.

Once again, a bulk execution with all the datasets is performed - unlike in Section B.5 there is minimum number to meet, so all the datasets can be treated generically.

The oversampling algorithm selected for this experiment has been SMOTE (see Section 2.3.1.2 for more information). Also, the same three classifiers used for the previous experiments are the ones used to compare results: (1) Naive Bayes - Gaussian; (2) Decission Tree; and (3) kNN Nearest Centroid.

```

1  ...
2  ...
3  import data as DATASETS
4
5  if __name__ == '__main__':
6      # Data
7      datasets = [
8          'ant',
9          'apache',
10         'camel',
11         'ivy',
12         'jedit',
13         'log4j',
14         'poi',
15         'synapse',
16         'xalan',
17         'xerces',
18         'hadoop-1',
19         'hadoop-2',
20         'hadoop-3',
21         'hadoop-4',
22         'hadoop-5',
23         'hadoop-6',
24         'hadoop-7',
25         'hadoop-8'
26     ]
27
28     for d in datasets:
29         print('-----' + d + '-----')
30         inputs, target = DATASETS.get_dataset(d)
31
32         # K-fold Parameters
33         k = 5
34         kf = KFold(n_splits=k)
35         splits = kf.split(inputs)
36         # Precision Recall Fallout Balanced F1 MCC AUC
37         mean_naive = np.array([0, 0, 0, 0, 0, 0, 0])
38         mean_tree = np.array([0, 0, 0, 0, 0, 0, 0])
39         mean_knn = np.array([0, 0, 0, 0, 0, 0, 0])
40
41         # Get measurements using K-fold
42         for train_index, test_index in splits:
43             # Data partition
44             x_train, x_test = inputs[train_index], inputs[test_index]

```

```

45     y_train, y_test = target[train_index], target[test_index]
46
47     filename = d + '-k' + str(k) + '-over'
48
49     # Train NN
50     # Pipeline to NN
51     print('---> Naive Bayes')
52     clf = make_pipeline(
53         SMOTE(),
54         GaussianNB())
55     predictions = DATASETS.train_predict(clf, x_train, y_train, x_test)
56     naive_metrics = DATASETS.calculate_results(y_test, predictions)
57     mean_naive = np.add(mean_naive, naive_metrics)
58     naive_metrics = ['Naive Bayes'] + naive_metrics
59     DATASETS.store_results(filename, naive_metrics)
60
61     print('---> Decision Tree')
62     clf = make_pipeline(
63         SMOTE(),
64         DecisionTreeClassifier())
65     predictions = DATASETS.train_predict(clf, x_train, y_train, x_test)
66     tree_metrics = DATASETS.calculate_results(y_test, predictions)
67     mean_tree = np.add(mean_tree, tree_metrics)
68     tree_metrics = ['Decision Tree'] + tree_metrics
69     DATASETS.store_results(filename, tree_metrics)
70
71     print('---> Nearest Centroid')
72     clf = make_pipeline(
73         SMOTE(),
74         NearestCentroid())
75     predictions = DATASETS.train_predict(clf, x_train, y_train, x_test)
76     knn_metrics = DATASETS.calculate_results(y_test, predictions)
77     mean_knn = np.add(mean_knn, knn_metrics)
78     knn_metrics = ['Nearest Centroid'] + knn_metrics
79     DATASETS.store_results(filename, knn_metrics)
80
81     print('-----')
82
83     # K-fold Mean
84     mean_naive = [round(i, 4) for i in (mean_naive / k)]
85     DATASETS.store_results(filename, ['Naive Bayes Mean'] + mean_naive)
86     mean_tree = [round(i, 4) for i in (mean_tree / k)]
87     DATASETS.store_results(filename, ['Decision Tree Mean'] + mean_tree)
88     mean_knn = [round(i, 4) for i in (mean_knn / k)]
89     DATASETS.store_results(filename, ['Nearest Centroid Mean'] + mean_knn)
90
91     print([mean_naive, mean_tree, mean_knn])

```

Listing B.6: Calculate Metrics from Confusion Matrix to compare in-fold results after applying over-sampling filter

Appendix C

Tables

C.1. Complexity Metrics OO datasets

Table C.1: Complexity Metrics Analysis

<i>Measure</i>	<i>Metric</i>	<i>ant</i>	<i>apache</i>	<i>camel</i>	<i>ivy</i>	<i>jedit</i>	<i>log4j</i>	<i>synapse</i>	<i>xalan</i>	<i>xerces</i>
<i>Balance</i>	<i>C1</i>	0.7653	0.9895	0.7114	0.5108	0.1545	0.3953	0.9209	0.0944	0.8219
	<i>C2</i>	0.4701	0.0286	0.5429	0.7477	0.9543	0.8319	0.1944	0.9755	0.3826
<i>Correlation</i>	<i>C2</i>	0.2622	0.0891	0.1227	0.1879	0.0448	0.0804	0.2310	0.0663	0.2839
	<i>C3</i>	0.6338	0.7372	0.5763	0.5588	0.5324	0.5780	0.7762	0.5275	0.6338
	<i>C4</i>	0.7409	1.0000	1.0000	0.3722	0.0285	0.4341	0.9727	0.0000	0.8878
<i>Dimensionality</i>	<i>T2</i>	0.0268	0.0524	0.0207	0.0568	0.0407	0.0976	0.0781	0.0220	0.0340
	<i>T3</i>	0.0027	0.0105	0.3000	0.0057	0.0020	0.0098	0.0078	0.0022	0.0034
<i>Linearity</i>	<i>L1</i>	0.2477	0.3937	0.2774	0.1570	0.0475	0.1426	0.3139	0.0285	0.3050
	<i>L2</i>	0.1212	0.1917	0.1370	0.0726	0.0200	0.0624	0.1534	0.0117	0.1342
	<i>L3</i>	0.1103	0.1828	0.1304	0.0661	0.0180	0.0593	0.1421	0.0110	0.1211
<i>Neighborhood</i>	<i>N1</i>	0.3208	0.3822	0.3565	0.2159	0.0447	0.2195	0.4023	0.0396	0.2789
	<i>N2</i>	0.3588	0.3232	0.3629	0.3285	0.2543	0.3588	0.3780	0.1615	0.2667
	<i>N3</i>	0.2067	0.1937	0.2435	0.1364	0.0325	0.1220	0.2422	0.0121	0.1173
	<i>N4</i>	0.0913	0.1728	0.1358	0.0739	0.0122	0.0293	0.0859	0.0308	0.0833
	<i>T1</i>	0.0025	0.0135	0.0021	0.0082	0.0184	0.0161	0.0072	0.0294	0.0057
	<i>LSC</i>	0.9860	0.9659	0.9923	0.9533	0.8870	0.9476	0.9797	0.8329	0.9601
<i>Network</i>	<i>Density</i>	0.8658	0.8801	0.8627	0.8293	0.8170	0.8260	0.8805	0.8165	0.8530
	<i>ClsCoef</i>	0.3377	0.2232	0.3131	0.3564	0.3314	0.4158	0.3143	0.3460	0.3429
	<i>Hubs</i>	0.7665	0.9236	0.7608	0.7628	0.8789	0.8487	0.9300	0.8564	0.8499
<i>Overlap</i>	<i>F1</i>	0.9192	0.9776	0.9825	0.9432	0.9874	0.9922	0.9438	0.9973	0.9496
	<i>F1v</i>	0.2882	0.4659	0.5203	0.2083	0.2048	0.3223	0.3313	0.3274	0.3118
	<i>F2</i>	0.0000	0.0061	0.0004	0.0005	0.0000	0.0000	0.0065	0.0000	0.0000
	<i>F3</i>	0.9074	0.9476	0.9513	0.7102	0.5915	0.6585	0.9141	0.3399	0.8129
	<i>F4</i>	0.8295	0.8325	0.8487	0.3977	0.0671	0.1659	0.7227	0.0055	0.6990
<i>Smoothness</i>	<i>S1</i>	0.2191	0.2474	0.2541	0.1453	0.0285	0.1520	0.2824	0.0319	0.2010
	<i>S2</i>	0.1410	0.1178	0.1389	0.1460	0.1417	0.1556	0.1638	0.1538	0.1479
	<i>S3</i>	0.2067	0.1937	0.2466	0.1364	0.0325	0.1220	0.2422	0.0121	0.1122

Continued on next page

Table C.1 – Continued from previous page

<i>Measure</i>	<i>Metric</i>	<i>ant</i>	<i>apache</i>	<i>camel</i>	<i>ivy</i>	<i>jedit</i>	<i>log4j</i>	<i>synapse</i>	<i>xalan</i>	<i>xerces</i>
	<i>S4</i>	0.0847	0.1273	0.1608	0.0716	0.0215	0.0285	0.1300	0.0209	0.1056

C.2. Complexity Metrics Hadoop datasets

Table C.2: Complexity Metrics Analysis on Hadoop datasets

<i>Measure</i>	<i>Metric</i>	<i>Hadoop 0.1</i>	<i>H 0.2</i>	<i>H 0.3</i>	<i>H 0.4</i>	<i>H 0.5</i>	<i>H 0.6</i>	<i>H 0.7</i>	<i>H 0.8</i>
Balance	<i>C1</i>	0.9381	0.7600	0.8132	0.7395	0.6589	0.5642	0.7056	0.3534
	<i>C2</i>	0.1559	0.4777	0.3970	0.5062	0.6056	0.7015	0.5501	0.8579
Correlation	<i>C2</i>	0.2868	0.0520	0.3171	0.1899	0.1601	0.1705	0.1997	0.1241
	<i>C3</i>	0.7741	0.6006	0.6330	0.5956	0.5589	0.5397	0.5737	0.4917
	<i>C4</i>	1.0000	1.0000	0.9810	1.0000	1.0000	0.7692	0.9720	0.2125
Dimensionality	<i>T2</i>	0.0496	0.0366	0.0332	0.0348	0.0322	0.0299	0.0280	0.0292
	<i>T3</i>	0.0142	0.0052	0.0095	0.0050	0.0046	0.0042	0.0040	0.0042
Linearity	<i>L1</i>	0.3770	0.3327	0.2658	0.2950	0.2620	0.1996	0.2654	0.1134
	<i>L2</i>	0.1870	0.1664	0.1305	0.1473	0.1310	0.0981	0.1327	0.0550
	<i>L3</i>	0.1832	0.1644	0.1055	0.1408	0.1274	0.0875	0.1254	0.0489
Neighborhood	<i>N1</i>	0.4965	0.4712	0.4028	0.4378	0.4009	0.3333	0.3840	0.1708
	<i>N2</i>	0.3474	0.4611	0.3151	0.4207	0.3960	0.3457	0.3682	0.3151
	<i>N3</i>	0.2553	0.3037	0.2417	0.3234	0.2857	0.1838	0.2200	0.1208
	<i>N4</i>	0.2411	0.2408	0.1374	0.1990	0.1429	0.1282	0.0960	0.0417
	<i>T1</i>	0.0127	0.0079	0.0118	0.0101	0.0096	0.0100	0.0087	0.0143
	<i>LSC</i>	0.9755	0.9838	0.9686	0.9708	0.9725	0.9686	0.9786	0.9428
Network	<i>Density</i>	0.8678	0.8610	0.8478	0.8433	0.8430	0.8232	0.8426	0.8030
	<i>ClsCoef</i>	0.3965	0.4411	0.4281	0.4453	0.4398	0.4383	0.4435	0.4465
	<i>Hubs</i>	0.8595	0.9252	0.9305	0.9121	0.9152	0.8929	0.9074	0.8912
Overlap	<i>F1</i>	0.9129	0.9958	0.8365	0.9641	0.9643	0.9519	0.9370	0.9711
	<i>F1v</i>	0.5101	0.8483	0.3019	0.5797	0.6427	0.4057	0.4816	0.3269
	<i>F2</i>	0.1818	0.0508	0.0135	0.1107	0.3023	0.0257	0.0552	0.0329
	<i>F3</i>	0.8865	0.9791	0.9479	0.9900	0.9032	0.9530	0.9600	0.8750
	<i>F4</i>	0.6879	0.9215	0.8294	0.9453	0.8479	0.8846	0.9000	0.6875
Smoothness	<i>S1</i>	0.3643	0.3421	0.2952	0.3100	0.2778	0.2446	0.2731	0.1255
	<i>S2</i>	0.1465	0.0908	0.1134	0.1075	0.1108	0.1122	0.1043	0.0961
	<i>S3</i>	0.2411	0.3246	0.2417	0.3284	0.2857	0.1709	0.2080	0.1208
	<i>S4</i>	0.2003	0.1863	0.1552	0.1516	0.1646	0.1175	0.1631	0.0625

Appendix D

Figures

D.1. Complexity Metrics

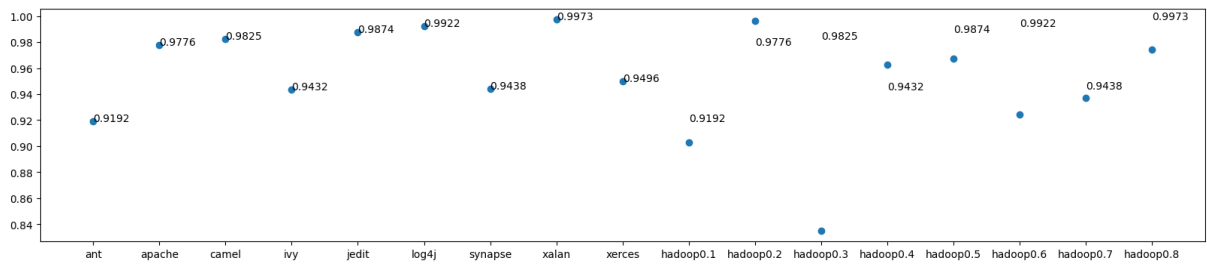


Figure D.1: Overlap F1

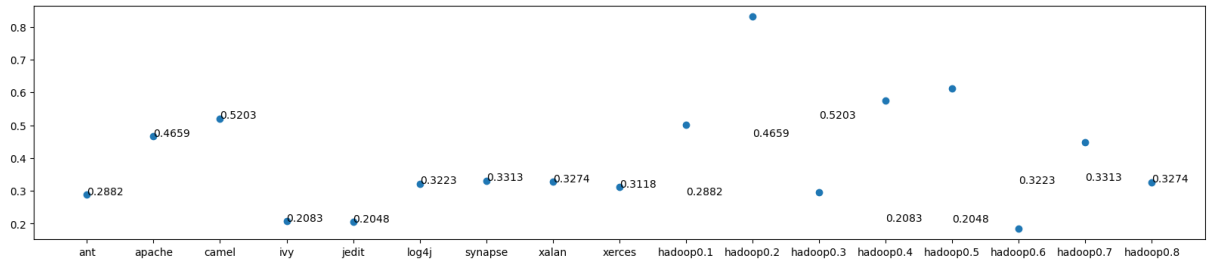


Figure D.2: Overlap F1v

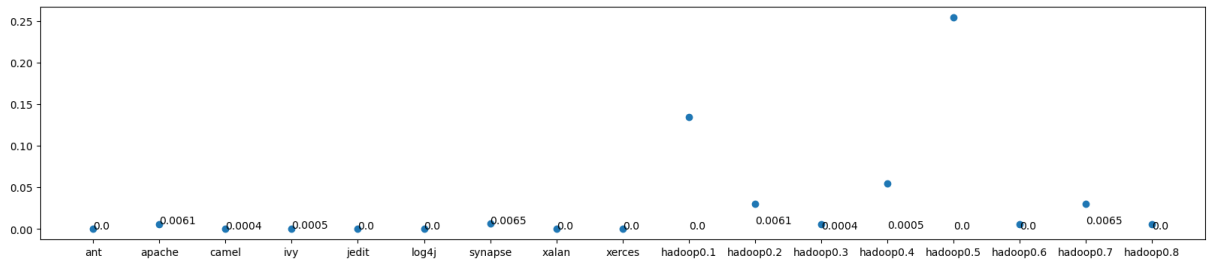


Figure D.3: Overlap F2

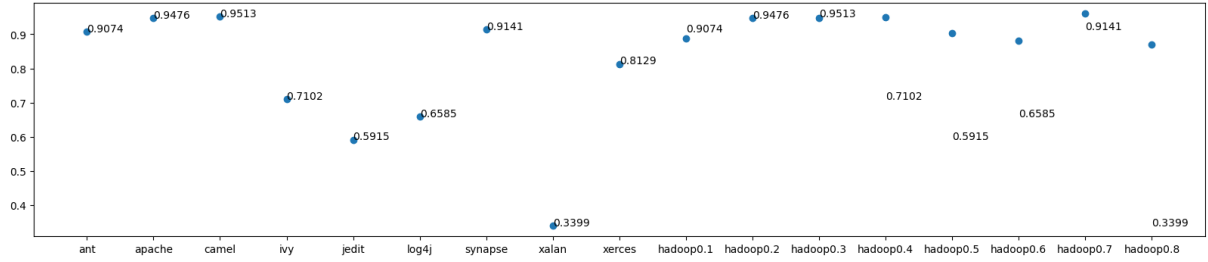


Figure D.4: Overlap F3

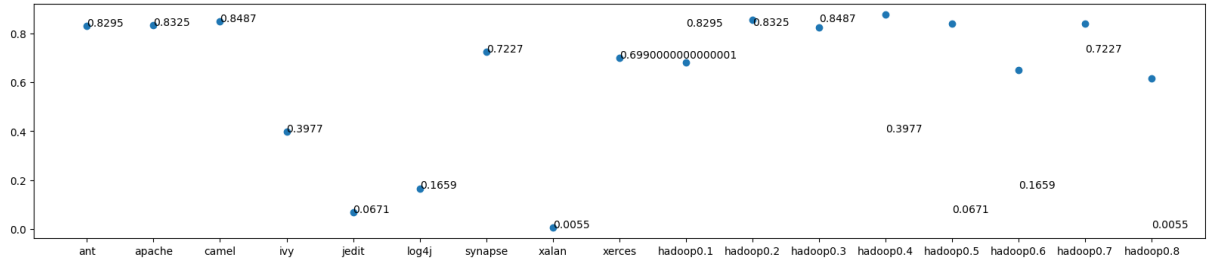


Figure D.5: Overlap F4

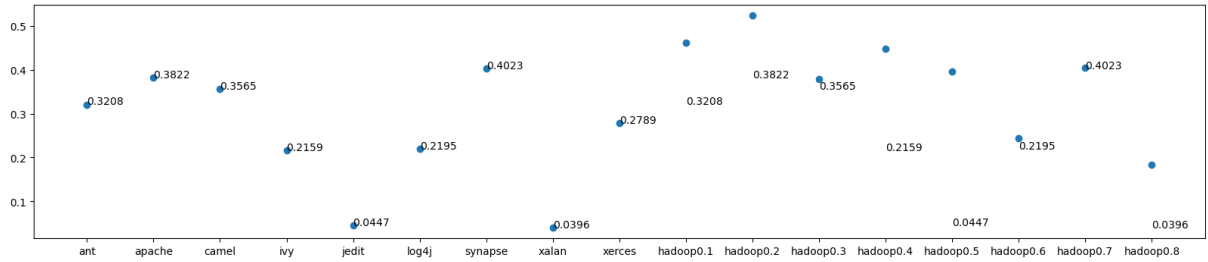


Figure D.6: Neighborhood N1

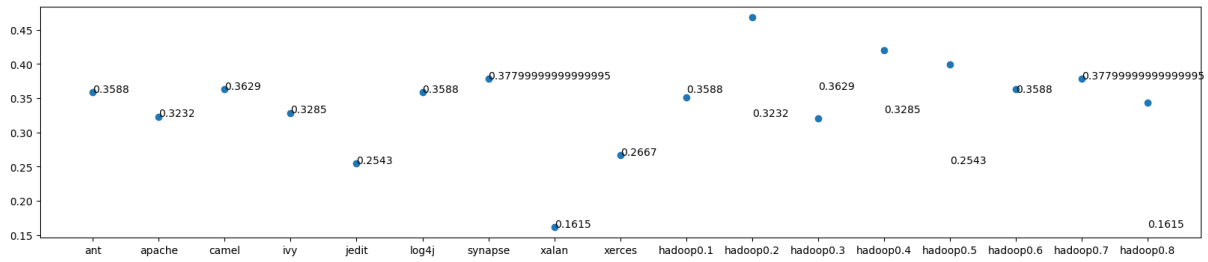


Figure D.7: Neighborhood N2

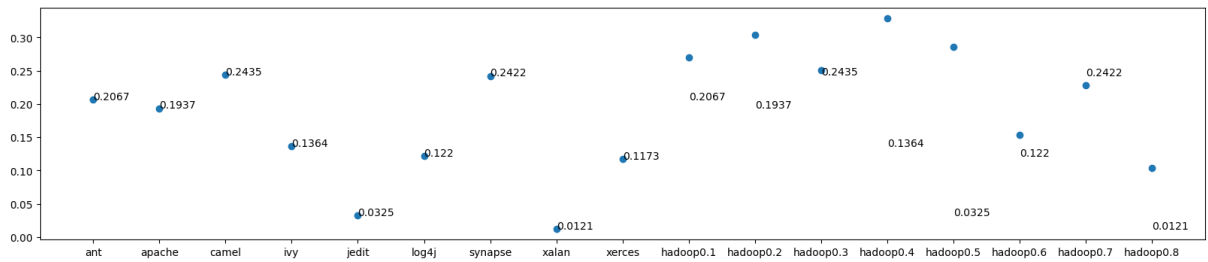


Figure D.8: Neighborhood N3

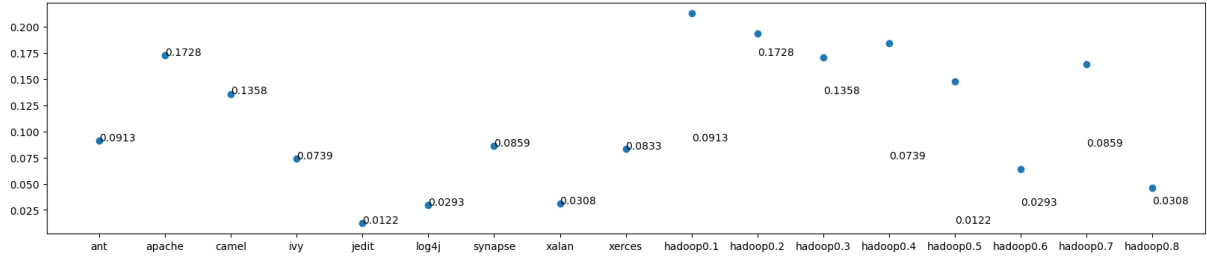


Figure D.9: Neighborhood N4

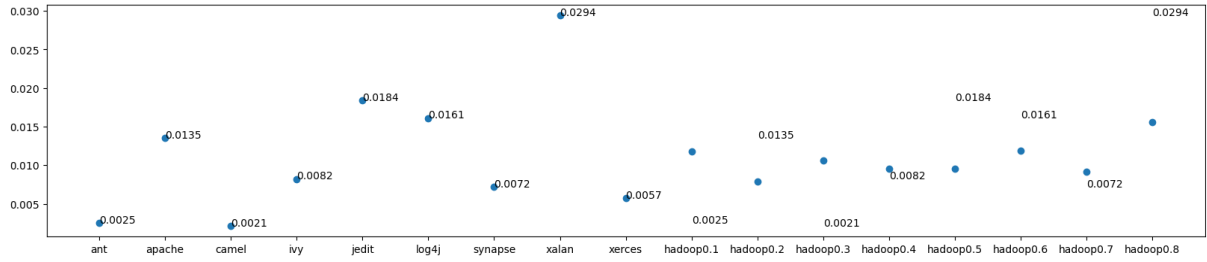


Figure D.10: Neighborhood T1

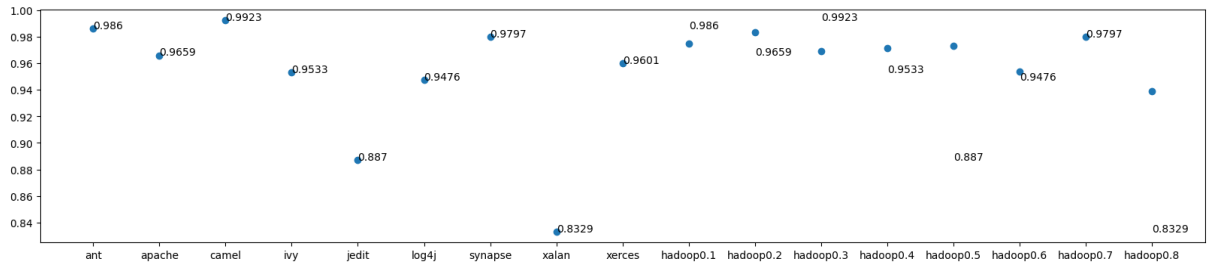


Figure D.11: Neighborhood LSC

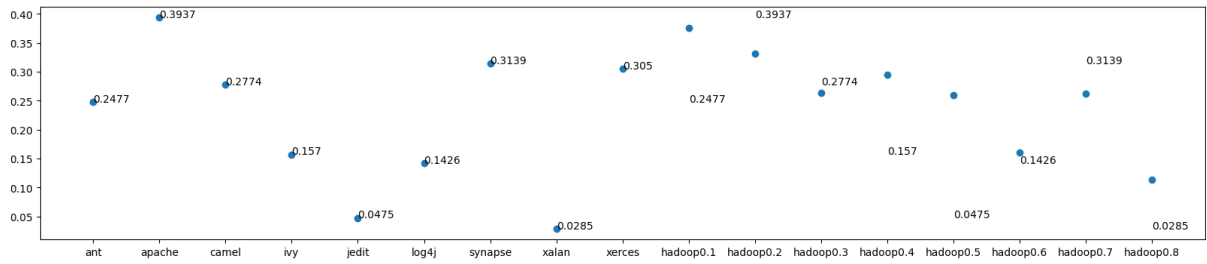


Figure D.12: Linearity L1

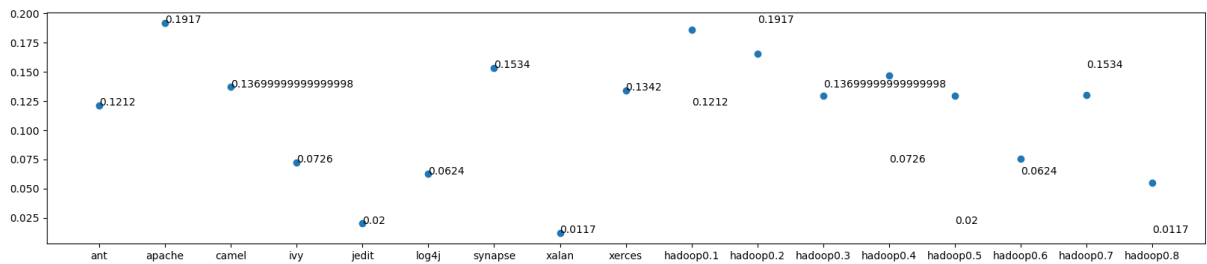


Figure D.13: Linearity L2

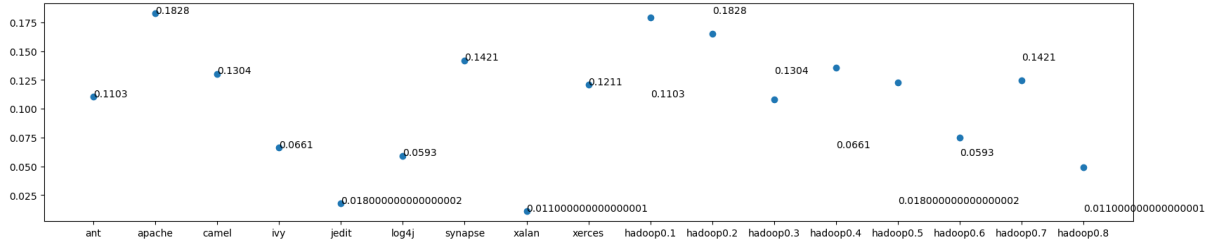


Figure D.14: Linearity L3

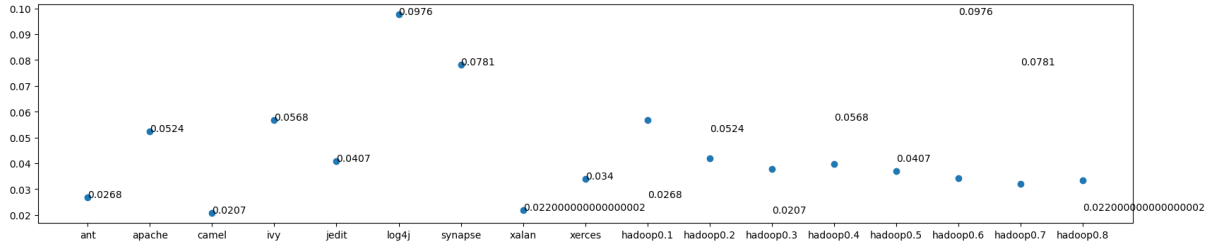


Figure D.15: Dimensionality T2

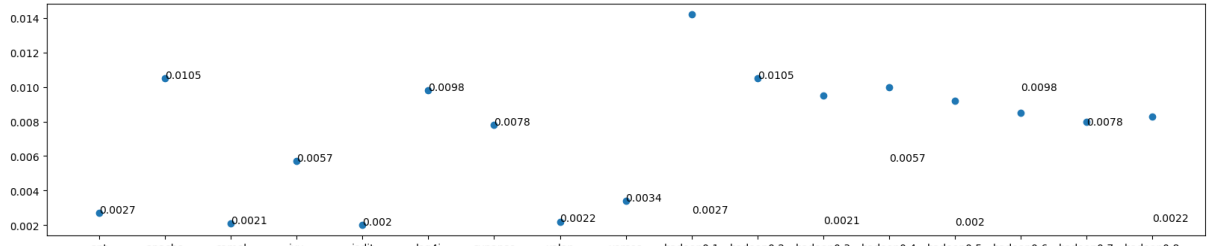


Figure D.16: Dimensionality T3

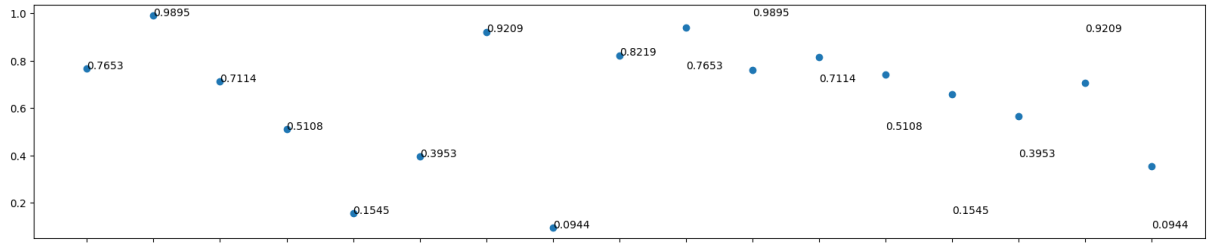


Figure D.17: Balance C1

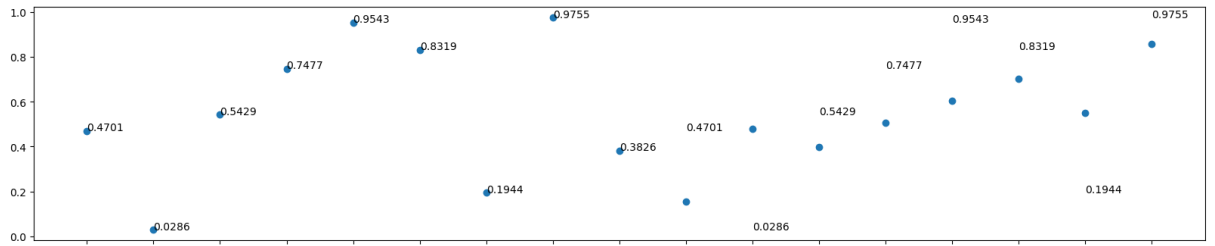


Figure D.18: Balance C2

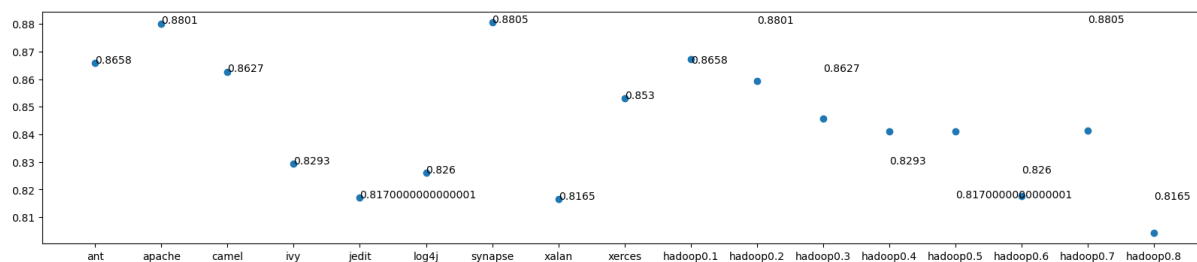


Figure D.19: Network Density

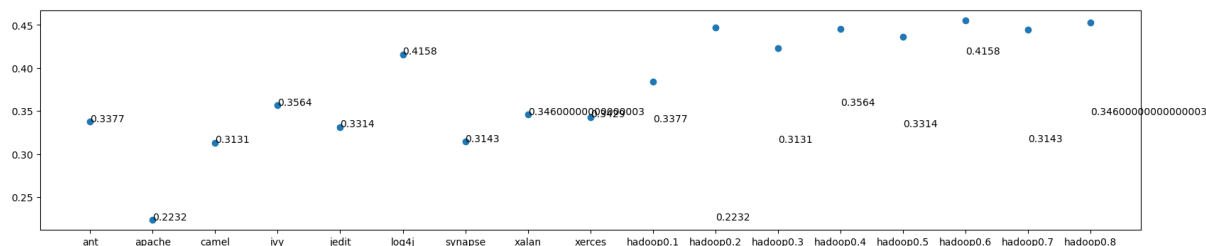


Figure D.20: Network ClsCoeF

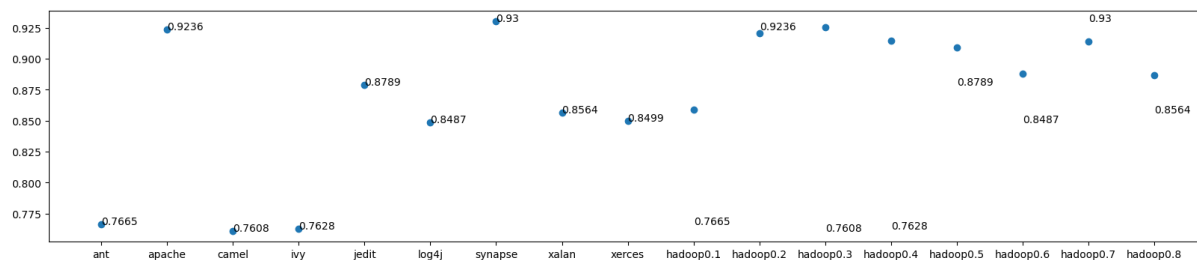


Figure D.21: Network Hubs

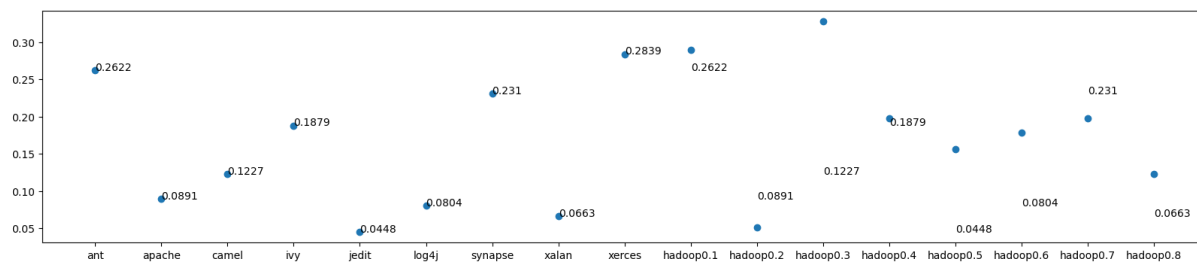


Figure D.22: Correlation C2

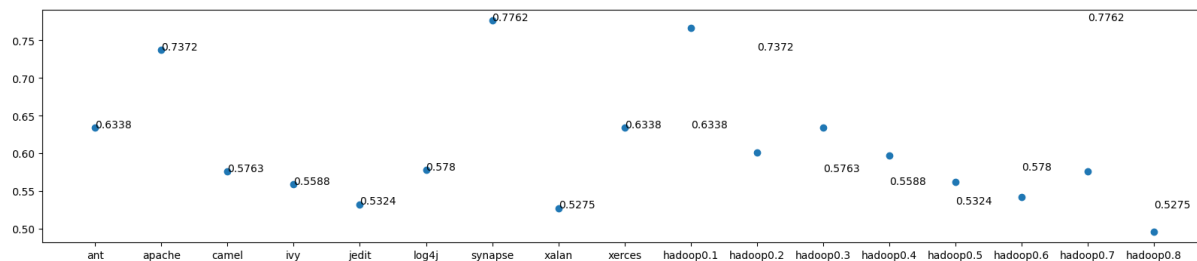


Figure D.23: Correlation C3

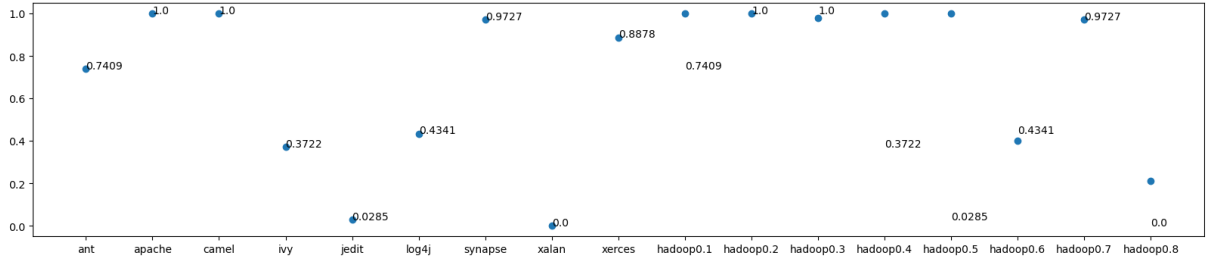


Figure D.24: Correlation C4

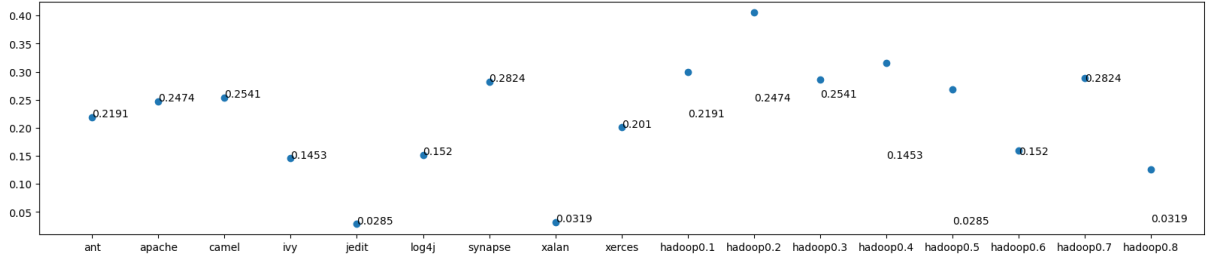


Figure D.25: Smoothness S1

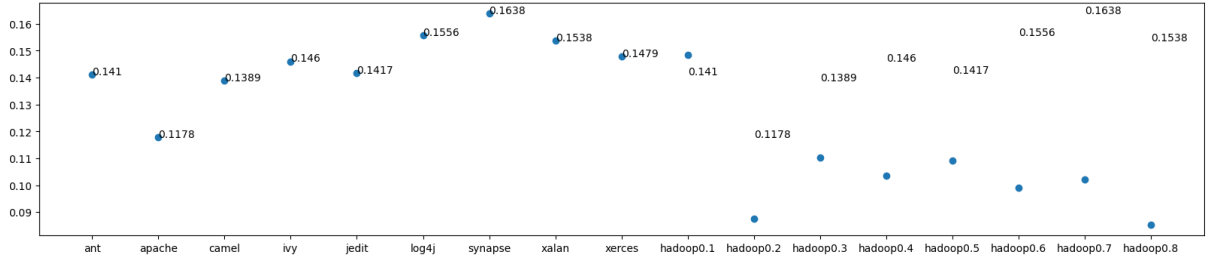


Figure D.26: Smoothness S2

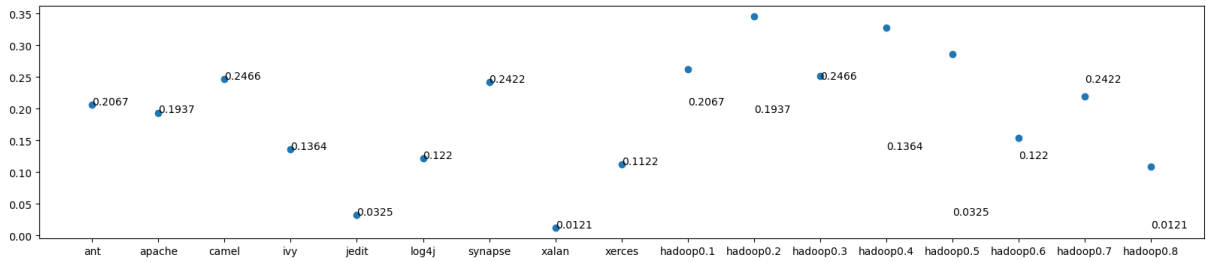


Figure D.27: Smoothness S3

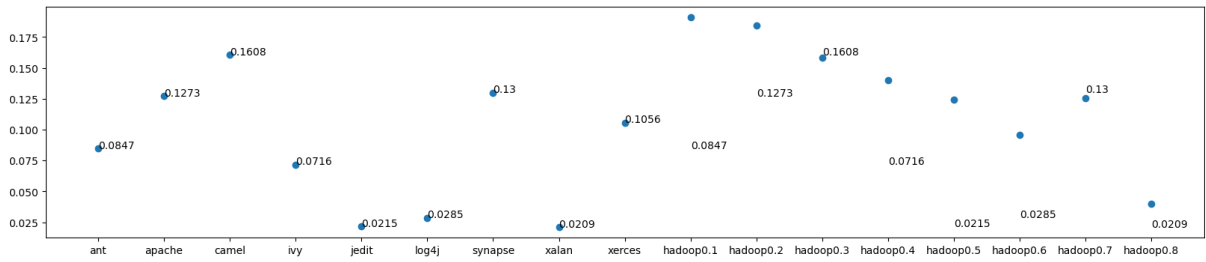


Figure D.28: Smoothness S4

Universidad de Alcalá
Escuela Politécnica Superior



ESCUELA POLITECNICA
SUPERIOR



Universidad
de Alcalá