

UNIVERSITÉ DE MONTRÉAL

RECOMMENDING WHEN DESIGN TECHNICAL DEBT SHOULD BE  
SELF-ADMITTED

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RECOMMENDING WHEN DESIGN TECHNICAL DEBT SHOULD BE  
SELF-ADMITTED

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**DEDICATION**

*À tous mes amis du labos,  
vous me manquerez... FACULTATIF*

## ACKNOWLEDGEMENTS

Texte. FACULTATIF

## RÉSUMÉ

Les Technical Debts (TD) sont des solutions temporaires et peu optimales introduites dans le code source d'un logiciel informatique pour corriger un problème rapidement au détriment de la qualité logiciel. Cette pratique est répandue pour diverses raisons: rapidité d'implémentation, conception initiale des composantes, connaissances faibles du projet, inexpérience du développeur ou pression face aux dates limites. Les TD peuvent s'avérer utiles à court terme, mais excessivement dommageables pour un logiciel et accaparantes au niveau du temps perdu. En effet, le temps requis pour corriger des problèmes et concevoir du code de qualité n'est souvent pas compatible avec le cycle de développement d'un projet. C'est pourquoi le sujet des TD a été analysé dans de nombreuses études déjà, plus spécifiquement dans l'optique de les détecter et les identifier.

Une approche populaire et récente est d'identifier les TD qui sont consciemment admises dans le code. La particularité de ces dettes, en comparaison aux TD, est qu'elles sont explicitement documentées par commentaires et intentionnellement introduites dans le code source. Les Self-Admitted Technical Debts (SATD) ne sont pas rares dans les projets logiciels et ont déjà été largement étudiées concernant leur diffusion, impact sur la qualité logiciel, criticité, évolution et acteurs. Diverses méthodes de détection sont présentement utilisées pour identifier les SATD mais toutes demeurent sujet amélioration. Par exemple, l'utilisation de mots clés (*e.g.*: *hack*, *fixme*, *todo*, *ugly*, *etc.*) dans les commentaires en relation avec les dettes techniques ou l'utilisation du Natural Language Processing (NLP) combiné à l'apprentissage machine. Donc, notre étude analyse dans quelle mesure des dettes techniques ayant déjà été consciemment admises (SATD) peuvent être utilisées pour fournir des recommandations aux développeurs lorsqu'ils écrivent du nouveau code. En d'autres termes, le but est d'être capable de suggérer quand admettre des dettes techniques ou quand améliorer du nouveau code en processus de rédaction.

Pour atteindre ce but, une approche d'apprentissage machine a été élaborée, nommée TEchnical Debt IdentificatiOn System (TEDIOUS), utilisant comme variables indépendantes divers types de métriques d'entrées au niveau des méthodes de manière à pouvoir classifier des dettes techniques de conception avec comme oracle des SATD connus. Le modèle a été entraîné et évalué sur neuf projets Java *open source* contenant des SATD précédemment étiquetés. En d'autres termes, notre approche vise à prédire précisément les TD dans les projets logiciels.

TEDIOUS fonctionne au niveau de granularité des méthodes, en d'autres termes, il dé-

tecte si une méthode contient une dette de conception ou non. Il a été conçu ainsi car les développeurs ont d'avantage tendance à admettre des dettes techniques au niveau des méthodes ou des blocs de code. Les TD peuvent être classifiés selon différents types: conception, requis, test, code et documentation. Les dettes de conception seulement ont été considérées car elles forment la majorité et analyser chaque type demanderait une analyse personnalisée.

TEDIOUS est entraîné avec des données étiquetées comme étant des SATD ou non et testé avec des données sans étiquettes. Les données étiquetées contiennent des méthodes marquées comme étant des SATD, obtenues à partir de neuf projets logiciels analysés par un autre groupe de recherche utilisant une approche NLP et validé manuellement. Les projets sont de différentes dimensions (*e.g.*: number of classes, methods, comments, etc.) et contiennent différentes proportions de dettes de conception. Des métriques sont extraits des données étiquetées: métriques de code source, métriques de lisibilité et alertes générées par des outils d'analyse statiques. Neuf métriques de code source ont été retenus pour fournir un portrait de la dimension, du couplage, de la complexité et du nombre de composantes des méthodes. La métrique de lisibilité prend en considération, entre autres, les retraits, la longueur des lignes et des identifiants. Deux outils d'analyse statique ont été utilisés pour cerner de faibles pratiques de codage.

Le prétraitement des métriques est appliqué pour retirer ceux étant superflus et garder ceux étant les plus pertinents par rapport à la variable dépendante. Certaines caractéristiques sont fortement corrélées entre elles et il serait redondant de toutes les conserver. D'autres subissent aucune ou trop de variations dans le contexte de notre ensemble de données, elles ne seraient pas utiles pour concevoir un prédicteur et sont donc supprimées également. De plus, les métriques sont normalisées pour atteindre des valeurs de performance appréciables au niveau de la prédiction inter-projets. Cette normalisation est nécessaire car le code source des projets varie en termes de dimensions et complexité. Finalement, l'ensemble de données est déséquilibré, ce qui signifie que le nombre de méthodes étiqueté comme étant un SATD est faible. Un suréchantillonnage a été appliqué sur la classe en minorité pour générer de nouvelles instances artificielles à partir de celles existantes.

Les modèles d'apprentissage machine sont construits à partir de l'ensemble d'entraînement et les prédictions sont évaluées à partir de l'ensemble de test. Cinq types de *machine learners* ont été testés: Decision Trees (J48), Bayesian classifiers, Random Forests, Random Trees and Bagging with Decision Trees. Ces modèles ont été retenus pour obtenir une grande variété de résultats, provenant de différents algorithmes considérés comme étant les plus appropriés et précis dans le contexte de notre étude.

Globalement, le but de notre étude est d'évaluer la performance de prédiction des SATD

selon notre approche. La vision poursuivie est de favoriser une meilleure compréhension et maintenabilité du code source. La perspective est d’être capable de suggérer quand admettre un TD ayant été identifié précédemment. Trois questions de recherche sont abordées:

- **RQ1:** Comment TEDIOUS performe dans la recommandation de SATD intra-projet?
- **RQ2:** Comment TEDIOUS performe dans la recommandation de SATD inter-projet?
- **RQ3:** Comment un *smell detector* au niveau des méthodes se compare avec TEDIOUS?

Pour répondre à **RQ1**, une validation croisée de dix échantillons a été réalisé sur tous les projets, ce qui signifie que chaque modèle est entraîné sur 90% de toutes les méthodes d’un projet et testé sur 10% de ceux-ci. Le processus est répété dix fois pour réduire l’effet du hasard. Une approche similaire est suivie pour **RQ2**, un modèle est entraîné avec 8 projets et testé avec 1.

Pour évaluer la performance de TEDIOUS, des métriques standards tels que la précision, le rappel et la mesure F1 sont calculés sur la classe SATD. Ces métriques sont basées sur la quantité de vrais positifs, faux positifs et faux négatifs. Pour compléter cette évaluation, la précision, le Matthews Correlation Coefficient (MCC) et le Receiving Operating Characteristics (ROC) Area Under the Curve (AUC) sont calculés, en partie pour tenir compte du nombre de vrais négatifs. Ce qui est visé comme performance des modèles d’apprentissage est un équilibre entre précision et rappel, de suggérer *correctement* le plus grand nombre possible de TD à admettre. MCC et AUC sont des indicateurs utiles pour réduire l’effet du hasard. L’importance des métriques d’entrées est aussi considérée pour évaluer les modèles.

Pour répondre à **RQ3**, la performance d’un *smell detector*, DETECTION & CORRECTION (DECOR), a été évalué selon sa capacité à classifier des méthodes étiquetées SATD comme étant des dettes techniques. Des odeurs au niveau des méthodes seulement ont été analysées, tout comme TEDIOUS. Finalement, quelques faux positifs et faux négatifs ont été discuté qualitativement pour exprimer les limites de notre approche.

Pour *RQ1*, les résultats ont démontré que le classificateur Random Forest a atteint les meilleures performances dans la recommandation de dettes de conception. La précision moyenne ayant été obtenue est 49.97% et le rappel 52.19%. Les valeurs de MCC et AUC pour chaque projet indiquaient la présence de classificateur de qualité. Équilibrer l’ensemble de données a permis d’accroître le rappel au détriment de la précision. La lisibilité, complexité et taille du code source ont joué un rôle significatif dans l’élaboration des prédictors.

Pour *RQ2*, la prédiction inter-projet augmente la performance des prédictors en comparaison à la validation croisée sur des projets singuliers, grâce à un ensemble d’entraînement

plus large et diversifié. La précision moyenne ayant été obtenue est 67.22% et le rappel 54.89%. Les valeurs de MCC et AUC indiquaient encore une fois la présence de classificateurs de qualité. Encore une fois, la lisibilité, la taille et la complexité ont joué un rôle important dans l'élaboration des prédicteurs.

Pour *RQ3*, Long Method (LM) et Long Parameter List (LP) été évalués par DECOR, de manière similaire aux métriques Lines Of Code (LOC) et nombre de paramètres, qui ont joué un rôle important dans l'entraînement des machines d'apprentissage. Toutefois, les performances de DECOR ne se sont pas avérées aussi bonnes que pour TEDIOUS. Le score  $F_1$  pour l'union de LM et LP n'a pu surpasser 22% et la valeur MCC indiquait une faible corrélation de prédiction.

Nous avons déjà conçu et testé une nouvelle approche pour améliorer la performance de TEDIOUS. Elle est similaire à la précédente car elle est basée sur l'apprentissage machine, elle fonctionne au niveau des méthodes et elle utilise des méthodes étiquetées comme des SATD de conception. Toutefois, le modèle de système d'apprentissage favorisé est le Convolutionnal Neural Network (CNN), implémenté spécifiquement pour le contexte de notre étude. Les variables indépendantes ne sont pas des caractéristiques du code source mais plutôt le code source *lui-même*. Comme les caractéristiques de l'approche précédente, le code source a aussi été prétraité, il a été transformé en jetons et un *word embedding* a été réalisé. Le CNN a été testé sur le même ensemble de données, intra-projet et inter-projet, mais aussi selon différentes variables indépendantes, code source avec, sans et partiellement avec commentaires. Une méthode d'analyse similaire a aussi été suivie, utilisant la validation croisée et les métriques de performance standards. **EDIT The performance values were ... and ... They were better than TEDIOUS in the way that ... Donner un aperçu de tous les resultats ... EDIT**

Ce mémoire décrit TEDIOUS, une approche d'apprentissage machine au niveau des méthodes conçu pour recommander quand un développeur devrait admettre un TD de conception, basé sur la taille, la complexité, la lisibilité et l'analyse statique du code source. Pour l'approche utilisant les caractéristiques du code source, les performances intra-projet basées sur 9 projets Java *open source* ont mené à des résultats prometteurs: environ 50% de précision, 52% de rappel et 93% de justesse. Les performances inter-projet se sont avérées encore meilleures: environ 67% de précision, 55% de rappel et 92% de justesse. L'ensemble de données grandement déséquilibré a représenté le plus grand obstacle dans l'obtention de valeurs de performance élevées. Pour les projets les plus volumineux, une précision et un rappel supérieurs à 88% ont été obtenus. Pour l'approche utilisant le code source lui-même, **EDIT The performance values were ... and ... They were better than TEDIOUS**



**in the way that ... Donner un appercu de tous les resultats ... EDIT**

TEDIOUS pourrait être utilisé pour diverses applications. Il pourrait être utilisé comme système de recommandation pour savoir quand documenter des TD nouvellement introduits. Deuxièmement, il pour aider à personnaliser les alertes relevées pour les outils d'analyse statique. Troisièmement, il pourrait compléter des détecteurs d'odeurs préexistants pour améliorer leur performance, comme DECOR. Quant aux travaux futurs, un plus grand ensemble de données sera étudié pour savoir si ajouter d'avantage d'information est bénéfique pour les performances de notre approche. De plus, nous planifions d'étendre TEDIOUS à la recommandation de plus de types de dettes techniques.

## ABSTRACT

TD are temporary solutions, or workarounds, introduced in portions of software systems in order to fix a problem rapidly at the expense of quality. Such practices are widespread for various reasons: rapidity of implementation, initial conception of components, lack of system's knowledge, developer inexperience or deadline pressure. Even though technical debts can be useful on a short term basis, they can be excessively damaging and time consuming in the long run. Indeed, the time required to fix problems and design code is frequently not compatible with the development life cycle of a project. This is why the issue has been tackled in various studies, specifically in the aim of detecting these harmful debts.

One recent and popular approach is to identify technical debts which are self-admitted. The particularity of these debts, in comparison to TD, is that they are explicitly documented with comments and intentionally introduced in the source code. SATD are not uncommon in software projects and have already been extensively studied concerning their diffusion, impact on software quality, criticality, evolution and actors. Various detection methods are currently used to identify SATD but are still subject to improvement. For example, using keywords (*e.g.*: *hack*, *fixme*, *todo*, *ugly*, *etc.*) in comments linking to a technical debt or using NLP in addition to machine learners. Therefore, this study investigates to what extent previously self-admitted technical debts can be used to provide recommendations to developers writing new source code. The goal is to be able to suggest when to "self-admit" technical debts or when to improve new code being written.

To achieve this goal, a machine learning approach was conceived, named TEDIOUS, using various types of method-level input features as independent variables to classify design technical debts using self-admitted technical debts as oracle. The model was trained and assessed on nine open source Java projects which contained previously tagged SATD. In other words, our proposed machine learning approach aims to accurately predict technical debts in software projects.

TEDIOUS works at method-level granularity, in other words, it can detect whether a method contains a design debt or not. It was designed this way because developers are more likely to self-admit technical debt for methods or blocks of code. TD can be classified in different types: design, requirement, test, code or documentation. Only design debts were considered because they represent the largest fraction and each type would require its own analysis.

TEDIOUS is trained with *labeled data*, projects with labeled SATD, and tested with

*unlabeled data*. The labeled data contain methods tagged as SATD which were obtained from nine projects analyzed by another research group using a NLP approach and manually validated. Projects are of various sizes (*e.g.*: number of classes, methods, comments, etc.) and contain different proportions of design debts. From the labeled data are extracted various kinds of metrics: source code metrics, readability metrics and warnings raised by static analysis tools. Nine source code metrics were retained to capture the size, coupling, complexity and number of components in methods. The readability metric takes in consideration indents, lines and identifiers length just to name a few features. Two static analysis tools are used to check for poor coding practices.

Feature preprocessing is applied to remove unnecessary features and keep the ones most relevant to the dependent variable. Some features are strongly correlated between each others and keeping all of them is redundant. Other features undergo important or no variations in our dataset, they would not be useful to build a predictor and thus are removed as well. Additionally, to achieve good cross-project predictions, metrics are normalized because the source code of different projects can differ in terms of size and complexity. Finally, the dataset is unbalanced, which means the amount of methods labeled as SATD is small. Over-sampling was applied on the minority class to generate artificial instances from the existing ones.

Machine learnings models are built based on the training set and predictions are evaluated from the test set. Five kinds of machine learners were tested: Decision Trees (J48), Bayesian classifiers, Random Forests, Random Trees and Bagging with Decision Trees. These models were retained to gather a wide variety of results, from different algorithms which were considered the most appropriate and accurate for the context of this study.

Globally, the goal of this study is to assess the SATD prediction performance of our approach. The quality focus is understandability and maintainability of the source code, achieved by tracking existing TD. The perspective is to be able to suggest when to admit those TD. Three research questions are aimed to be addressed:

- **RQ1:** How does TEDIOUS work for recommending SATD within-project?
- **RQ2:** How does TEDIOUS work for recommending SATD across-project?
- **RQ3:** How would a method-level smell detector compare with TEDIOUS?

To address **RQ1**, 10-fold cross validation was performed on all projects, which means a machine learner is trained with 90% of a project's methods and tested with 10% of them. The process is repeated 10 times to reduce the effect of randomness. A similar approach is used for **RQ2**, a machine learner is trained with 8 projects and is tested with 1 project.

To assess the performance of TEDIIOUS, standard metrics such as precision, recall and F1 score are computed for the SATD category. These metrics are based on the amount of True Positive (TP), False Positive (FP) and False Negative (FN). To complement the evaluation, accuracy, MCC and ROC AUC are computed, partly to take into account the amount of True Negative (TN). What is aimed for in a machine learning model performance is a balance between precision and recall, to suggest as many *correct* TD to admit as possible. MCC and AUC are useful indicators to reduce the effect of chance. The importance of feature metrics is also taken into account to evaluate the models.

To address **RQ3**, the performance of a smell detector, DECOR, was computed and evaluated in classifying as TD methods labeled as SATD. Only method-level smells were analyzed, similarly to TEDIIOUS. Finally, some FP and FN were qualitatively discussed in order to explain the limits of our approach.

For **RQ1**, results showed that Random Forest classifiers achieved the best performance recommending design debts. The average precision obtained is 49.97% and the recall 52.19%. The MCC and AUC values of each project generally indicated healthy classifiers. Balancing the dataset increased recall at the expense of precision and code readability, complexity and size played a significant role in building the predictors.

For **RQ2**, cross-project prediction increased the performance of predictors compared to the standard cross-validation on singular projects because of a larger and more diverse training set. The average precision obtained is 67.22% and the recall 54.89%. The MCC and AUC values still indicated healthy classifiers. Similarly to within project predictions, code readability, size and complexity played the most important role in recommending when to self-admit design TD.

For **RQ3**, LM and LP were the specific smells targeted and evaluated by DECOR, similar to LOC and number of parameters metrics, which played an important role in training machine learners in the context of our study. However, the detectors of DECOR were unable to achieve similar performance as TEDIIOUS. The  $F_1$  score for the union of LM and LP couldn't surpass 22% and the MCC value leaned towards a low prediction correlation.

We already designed and tested a new approach in order to improve the performance of TEDIIOUS. It is similar to the previous one because it is machine learning based, it works at method-level and it uses design SATD tagged methods. However, the machine learning model favored is a CNN which was implemented for the context of our study. The independent variables are not source code features but rather the source code *itself*. Like features from the previous approach, the source code was also preprocessed, it was tokenized and a word embedding was performed. The CNN was tested using the same dataset, within-project and

across-project, but also using different independent features, source code with comments, without comments or partially with comments. A similar analysis method was followed, using cross validation and standard performance metrics. **EDIT The performance values were ... and ... They were better than TEDIOUS in the way that ... Donner un aperçu de tous les résultats ... EDIT**

This paper describes TEDIOUS, a method-level machine learning approach designed to recommend when a developer should self-admit a design technical debt based on size, complexity, readability metrics, and static analysis tools checks. For the approach using source code features, within-project performance values based on 9 open source Java projects lead to promising results: about 50% precision, 52% recall and 93% accuracy. Cross-project performance was even more promising: about 67% precision, 55% recall and 92% accuracy. Highly unbalanced data represented the biggest issue in obtaining higher performance values. For bigger projects, precision and recall above 88% were obtained. For the approach using the source code itself, **EDIT The performance values were ... and ... They were better than TEDIOUS in the way that ... Donner un aperçu de tous les résultats ... EDIT**

Different applications could be made of TEDIOUS. It could be used as a recommendation system for developers to know when to document TD they introduced. Secondly, it could help customize warnings raised by static analysis tools, by learning from previously defined SATD. Thirdly, it could compliment existing smell detectors to improve their performance, like DECOR. As for our future work, a larger dataset will be studied to see if adding more information could be beneficial to our approach. Additionally, we plan to extend TEDIOUS to the recommendation of more types of technical debts.

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## LIST OF SYMBOLS AND ABBREVIATION

TD	Technical Debt
SATD	Self-Admitted Technical Debt
NLP	Natural Language Processing
TEDIOUS	TEchnical Debt IdentificatiOn System
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
MCC	Matthews Correlation Coefficient
ROC	Receiving Operating Characteristics
AUC	Area Under the Curve
DECOR	DEtection & CORrection
LOC	Lines Of Code
LM	Long Method
LP	Long Parameter List
WMC	Weighted Method Complexity
CBO	Coupling Between Objects
CNN	Convolutionnal Neural Network
QMOOD	Quality Model for Object-Oriented Design
OO	Object-Oriented
HIST	Historical Information for Smell Detection
SVM	Support Vector Machines
ASAT	Automated Static Analysis Tools
OSS	Open Source Software
SMOTE	Synthetic Minority Over-sampling Technique
Pr	Precision
Rc	Recall
Acc	Accuracy
MDI	Mean Decrease Impurity
RNN	Recurrent Neural Network

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## CHAPTER 1 INTRODUCTION

In today's consumer society, products have to be designed and ready to hit the market as fast as possible in order to stand out from other similar products and generate sells. This pressure to produce can affect the quality, maintainability and functionality of the design. In software engineering, the repercussion of this mindset can be measured with the amount of technical debts present in a project. These TD can go unnoticed, which is the danger behind them, or may be admitted by developers. In fact, studies have been conducted on technical debts that are "self-admitted" by developers, commenting why such code represent an issue or a temporary solution. The subject of this paper is to study how previously self-admitted technical debts can be used to recommend when to admit a newly introduced TD.

### 1.1 Basic Concepts and Definitions

Technical debts are temporary and less than optimal solutions introduced in the code. They are portions of code that still need to be worked on even though they accomplish the purpose they were written for. As Cunningham first described them, TD is "not quite right code which we postpone making it right" (Cunningham, 1992). For example, TD could be workarounds which don't follow good coding practices, poorly structured or hard-to-read code. By definition, technical debts don't typically cause errors, preventing the code from working, but they can in some circumstances. Various reasons can motivate the introduction of technical debts: to rapidly fix an issue, development team is at the early stages of conception, lack of comprehension, skills or experience (Suryanarayana et al., 2015).

TD are introduced throughout the whole conception timeline and under various forms, partly because writing quality code is not always compatible with the standard development life cycle (Brown et al., 2010). An ontology and landscape have been built to better define the subject. Design, requirement, code, test and documentation debts represent the main branches of the classification tree (Alves et al., 2014; Izurieta et al., 2012). Each branch can be linked to a specific development stage and to specific criteria. For example, design debt "refers to debt that can be discovered by analyzing the source code by identifying the use of practices which violated the principles of good object-oriented design (e.g. very large or tightly coupled classes)" (Alves et al., 2014).

Other work investigated the perception of developers on technical debts. It was found that the most important source of TD is architectural decisions, that recognizing the phe-

nomenon is essential for communication and that there is a lack of tools to manage those debts (Ernst et al., 2015). Additionally, project teams recognize that this issue is unavoidable and necessary (Lim et al., 2012). Technical debts cause a lot of problems: slower conception and execution of the software product (Allman, 2012), worse software maintainability and quality (Wehaibi et al., 2016; Zazworka et al., 2011), and higher production cost (Guo et al., 2011).

Frequently, TD are introduced consciously and explicitly by developers. In those cases, they are "self-admitted" and explained in comments, describing what is wrong with the related block of code (Potdar and Shihab, 2014). Like TD, self-admitted technical debts are encountered in most software projects. It was found that 31% of files contain SATD, that they remain present for a long period of time and that more experienced developers have the tendency to introduce them (Potdar and Shihab, 2014). This proves that a proper management tool is required to deal with this issue, and that unexperienced developers would greatly benefit from such support in order to decide when code should be reworked and documented as TD. The disparity between the experienced and unexperienced workers may also lie in the fact that the unexperienced ones don't want to admit their faults in order to maintain a positive image towards their superiors.

Another study found that there is no clear correlation between code quality and SATD (Bavota and Russo, 2016). Code quality metrics such as Weighted Method Complexity (WMC), Coupling Between Objects (CBO) and Buse and Weimer Readability (Buse and Weimer, 2010) were computed and analyzed to reach this conclusion. However, the purpose of their work was not mainly to evaluate this relationship but rather to establish a taxonomy of TD. Some threats to the validity of their results could also be made concerning the number of manually analyzed SATD and the level at which the metrics were computed (class-level). A finer analysis would have been required because a single class can contain methods of different length, complexity, cohesion, coupling and readability. This same study found in the analyzed projects on average 51 instances of SATD (0.3% of all comments), that the developer who introduces a TD is generally the same that fixes it and that they aren't all fixed.

## 1.2 Elements of the Problematic

It is pretty clear that technical debts account for a lot of issues in the development of software applications. They have been extensively analyzed and classified in order to have a better understanding of their impact. However, the identification, as much as the *correct* identification, of SATD remains a struggle for researchers and developers. Current methods

can obtain up to 25% of their total predictions as FP (Bavota and Russo, 2016). This means that a quarter of all automatically identified TD are not really technical debts and that the previous studies could be based on wrong information. It is true that many strategies can be employed to reduce and fix the number of TD in a software project: take your time when implementing a solution, code refactoring, continuous tracking of TD, proactiveness in fixing debts, etc. (Ambler, 2013). However, they are not highly effective and they frequently rely on the willingness of developers to fix the problem and their general knowledge.

Better automatic approaches have been proposed to improve the detection of TD. One of them is to identify comment patterns that relate to self-admitted technical debts (Potdar and Shihab, 2014). Potdar *et al.* manually went through 101 762 comments to determine these patterns, which lead to the identification of 62 SATD patterns. Here are some examples: *hack*, *fixme*, *is problematic*, *this isn't very solid*, *probably a bug*. The main issue with this approach is the the manual process behind it, which introduces human error and subjectivity. Another approach is to use machine learning techniques, such as NLP, to automatically identify SATD using source code comments (Maldonado et al., 2017a). This idea is promising because it does not heavily depend on the manual classification of source code comments. In fact, it outperforms the previous approach. Manual classification is still required to build the training set for the NLP classifier. However, the model built from this dataset can then be used to automatically identify SATD in any project, thus removing any other manual analysis.

It is important to mention that our study does not revolve on proposing a new SATD detection method using information contained in comments, but rather using them as a base for our recommendation tool. Consequently, the proper classification of SATD used by TEDIOUS will directly affect its performance. To properly establish the problematic of our study, several research questions have to be addressed, the main one can be defined like this:

How can we identify and detect technical debts in a software project using source code features and known self-admitted technical debts in a machine learning approach?

This question can be divided into three others: How does TEDIOUS work for recommending SATD within-project? How does TEDIOUS work for recommending SATD across-project? How would a method-level smell detector compare with TEDIOUS? This approach is based on the hypothesis that current methods to detect technical debts are limited and inefficient and that a new approach could be beneficial to the improvement of detection performance. We also think that manual analysis and human subjectivity is detrimental to the efficiency of current methods. Consequently, we believe that a well crafted machine learning

approach could lead to better results and performance values in identifying technical debts and recommending when they should be self-admitted.

### 1.3 Research Objectives

The main objective of this research is to design a machine learning approach that uses as independent variables various kinds of source code features, and as dependent variables the knowledge of previously self-admitted technical debts, to train machine learners in recommending to developers when a technical debt should be admitted.

As mentioned previously, the purpose of this study is not to propose a novel method to identify SATD from source code comments, using patterns or NLP (Maldonado et al., 2017a; Potdar and Shihab, 2014). It is more about using results of these methods to build our training dataset. Our approach relies more on source code information and metrics to identify possible TD to self-admit.

The main objective can be divided in two purposes. Firstly, tracking and managing technical debts is considered important but lacking in the industry (Ernst et al., 2015). Consequently, TEDIOUS could be used to encourage developers to self-admit TD in order to easily track and fix the issue. This is particularly true for junior developers, who are less prone to doing so than experienced ones (Potdar and Shihab, 2014). Secondly, our tool could be used as an alternative, or a complement, to existing smell detectors in proposing improvements to source code. In other words, TEDIOUS could act as a tracking, managing and improvement tool for software projects.

The general objective can be divided in specific objectives. The first one aims at *defining and extracting relevant features from methods*. These features are the characteristics that describe each method. In contrary to previous studies (Bavota and Russo, 2016), TEDIOUS works at method-level rather than class-level because we found that SATD comments are more frequently related to methods or blocks of code. Features can be: a set of structural metrics extracted from methods, the method’s readability or warning raised by static analysis tools.

The second specific objective aims at *identifying self-admitted technical debts*. Only a certain type of technical debt is considered, namely design debts, for various reasons. Firstly, it is the most common type of TD (Maldonado et al., 2017a). Secondly, the other types (requirement, code, test and documentation) would require a different analysis and features. However, adding these types is part of our future work. No real detection method is used to



detect those SATD, instead, design related TD from a previously annotated dataset consisting of 9 Java open source projects are used (Maldonado et al., 2017a).

The third specific objective aims at *preprocessing the features*. Strongly correlated features are cleaned up to remove redundancy, metrics that don't vary or vary too much are also removed, a normalization is applied to take into account the different nature of projects and the training set is balanced by oversampling the small number of SATD tagged methods.

The fourth specific objective aims at *building and applying machine learning models*. Five machine learners are trained and tested, performing SATD prediction within-project and across-project. The five retained are: Decision Trees (J48), Bayesian classifiers, Random Forests, Random Trees and Bagging with Decision Trees.

We could add another objective which would aim at *improving the first TEDIOUS approach*. To do so, a Convolutional Neural Network is designed and implemented, using the source code itself as the independent variable. It is tested using the same dataset, within-project and across-project, and with different independent variable configurations, with, without or partially with comments. The results show improvement compared to the previous approach, **EDIT The performance values were ... and ... They were better than TEDIOUS in the way that ... Donner un aperçu de tous les résultats ... EDIT**

## 1.4 Thesis Overview

**Chapter 2: Literature Review** The literature review provides a current state-of-the-art overview of the knowledge on technical debts and other related topics. It summarizes relevant information extracted from previous studies concerning four main topics: relationship between technical debt and source code metrics, self-admitted technical debt, code smell detection and automated static analysis tools.

**Chapter 3: The Approach and Study Definition** The approach followed is thoroughly described in four sections. The types of features are described and the way they are extracted is explained. The provenance and identification of the SATD tagged comments is shared. The preprocessing that is performed on features is demystified and justified. The machine learning models chosen are revealed as well as their configuration. As for the study definition, the dataset characteristics (number of files, classes, comments, etc.) are shared for each project and the analysis method (cross validation, accuracy, precision, recall,  $F_1$  score, MCC, ROC, AUC) explained.

**Chapter 4: Analysis of Study Results and Threats to Validity** The study results are analyzed based on each research question: performance for within-project prediction, performance for across-project prediction and comparison with a method-level smell detector. Results indicate that within-project prediction achieves at best 50% precision and 52% recall. Improvement is made for across-project prediction where prediction achieves at best 67% precision and 55% recall. The best machine learner turned out to be Random Forest. It was also found that SATD predictions made by TEDIIOUS only weakly relate to method-level code smells. A qualitative discussion on false positives and negatives is also proposed. Following the results analysis, several threats to validity are shared: construct, internal, conclusion and external validity threats.

**Chapter 5: Convolutional Neural Network with Comments and Source Code** This chapter describes an updated approach to detect TD to self-admit and its preliminary results. First, the CNN characteristics and features are described. Secondly, the approach is explained: the features used, the identification of SATD, the use of word embeddings and the way the CNN is built and applied to the context of our study. Thirdly, the study definition is described: the characteristics of the dataset and the analysis method. Finally, the study results are analyzed based on three prediction contexts: source code with comments, without comments and partially with comments. Various CNN configurations are also analyzed. **EDIT The performance values were ... and ... They were better than TEDIIOUS in the way that ... Donner un aperçu de tous les résultats ... EDIT**

## CHAPTER 2 LITERATURE REVIEW

The subject of this study can be divided in four relevant topics, which will be summarized in this chapter. The literature review introduces each topic based on previous studies and research papers. The first one addresses the relationship between technical debt and source code metrics. The second defines the nature of self-admitted technical debts. The last topic combines the code smell detection approaches and automated static analysis tools.

### 2.1 Relationship Between Technical Debt and Source Code Metrics

Many researchers have tried to relate technical debts, more specifically design and code, to source code metrics in order to detect them. One of the approach is based on a technique for detecting design flaws, built on top of a set of metric rules capturing coupling, cohesion and encapsulation (Marinescu, 2012). Another study empirically validated the relationship between TD and software quality models. Three TD detection methods were compared with Quality Model for Object-Oriented Design (QMOOD) (Bansiya and Davis, 2002) and only one of them had a strong correlation to quality attributes reusability and understandability (Griffith et al., 2014). Another team studied how five different tools detect technical debts, their principal features, differences and missing aspects (Fontana et al., 2016a). They focused on the impact of design smells on code debt to give advices on which design debt should be prioritized for refactoring. These tools all take into account metrics, smells, coding rules and architecture violations but there is only a limited agreement among them and they still ignore some important pieces of information.

### 2.2 Self-Admitted Technical Debt

Many studies have been conducted in order to describe and classify the nature of self-admitted technical debts. Potdar and Shihab (2014) investigated technical debts in the source code of open source projects and they found out that developers frequently self-admit TD they introduce, explaining why this particular block of code is temporary and needs to be reworked in the form of comments. They are some of the first to acknowledge the existence of SATD and to propose a detection method using pattern matching in source code comments. da S. Maldonado and Shihab (2015) analyzed developers' comments in order to examine and quantify the different types of SATD. A similar approach to Potdar and Shihab (2014) is followed, using pattern matching, to classify the SATD into five types: design, defect,

documentation, requirement and test. It was found that design debts are the most common, making up between 42% and 84% of all comments.

Bavota and Russo (2016) performed a large-scale empirical study on self-admitted technical debt in open source projects. They studied its diffusion and evolution, the actors involved in managing SATD and the relationship between SATD and software quality. They showed that there is on average 51 instances of SATD per system, that code debts are the most frequent, followed by defect and requirement debts, that the number of instances increases over time because they are not fixed by developers, and that they normally survive for a long time. Like Griffith et al. (2014), they found no real correlation between SATD and quality metrics (WMC, CBO, Buse and Weimer readability).

Wehaibi et al. (2016) also studied the relation between self-admitted technical debt and software quality. Their approach is based on investigating if more defects are present in files with more SATD, if SATD changes are more likely to cause the emergence of future defects and whether they are more difficult to perform. They found that no real trend was noticed between SATD and defects, SATD changes did not introduce more future defects compared to none SATD changes but they are indeed more difficult to perform.

A new approach based on NLP techniques was used recently to detect self-admitted technical debts, more specifically design and requirement debts (Maldonado et al., 2017a). They extracted comments from ten open source projects, cleaned them to remove the ones considered irrelevant and manually classified them into the different types of SATD. This dataset was then used as the training set for a maximum entropy classifier. It turned out that the model could accurately identify SATD and outperform the pattern matching method of Potdar and Shihab (2014). Comments mentioning sloppy or mediocre source code were the best indicators of design debts and comments related to partially implemented requirement were the best for requirement debts.

The detection of self-admitted technical debts is a major research approach in the study of SATD, however, this is not the purpose of our work. We do not propose a new approach using source code comments information, instead, we gather information about the structure of the code at method-level in order to recommend to developers when to self-admit technical debts.

## 2.3 Code Smell Detection and Automated Static Analysis Tools

Several approaches to detect code smells have been proposed in today's literature. Reading techniques have been created to guide developers in identifying Object-Oriented (OO) designs

(Travassos et al., 1999). Some formulate metrics-based rules as a detection strategy that can capture poor design practices (Marinescu, 2004) or use these software metrics to characterize bad smells (Munro, 2005). Others such as Moha et al. (2010) propose DECOR, an approach using rules and thresholds on various metrics. Many detection techniques rely on structural information, however, Palomba et al. (2015) exploited change history information to propose Historical Information for Smell Detection (HIST) to detect instances of five different code smells, with promising results. Fokaefs et al. (2011) used graph matching to propose JDeodorant, an Eclipse plugin that automatically applies refactoring on "God Classes". Using graph matching also, a methodology recommending "Move Method" refactoring opportunities for "Feature Envy" bad smells was also proposed to reduce coupling and increase cohesion (Tsantalis and Chatzigeorgiou, 2009). Lastly, machine learning techniques are also popular. Fontana et al. (2016b) compared and experimented 16 different machine learning algorithms to detect code smells, Khomh et al. (2009) proposed a Bayesian approach to detect code and design smells and Maiga et al. (2012) proposed SVMDetect, a new approach to detect anti-patterns using a Support Vector Machines (SVM) technique.

Our approach is different from these previous ones for two main reasons. Firstly, they use structural or historical information and metrics from the code to detect smells. In addition to these characteristics, we use feedback provided by developers, in the form of SATD comments which leads to the identification of technical debts. Secondly, we also use warnings generated by Automated Static Analysis Tools (ASAT) to portray an even better representation of the source code quality.

The subject of automated static analysis tools have already been widely covered to analyze its benefits on the development of software projects. The correlation and correspondence between post-release defects and warnings issued by the bug finding tool FindBugs was studied to understand the actual gains provided by ASAT (Couto et al., 2013). Only a moderate correlation was found and no correspondence between defects and raised warnings. On the other hand, three ASAT were evaluated by Wedyan et al. (2009) showing that they could successfully recommend refactoring opportunities to developers. FindBugs static analysis tool was also evaluated by Ayewah et al. (2007) to quantify its accuracy and the value of warnings raised. They found that warnings were mostly considered relevant by developers and that they were willing to make the appropriate modifications to fix the issues. Beller et al. (2016) performed a large-scale evaluation of ASAT in Open Source Software (OSS). They found that the use of ASAT is widespread but no strict usage policy is imposed in software projects. Generally, the automated static analysis tools are used with their default configuration, only a small amount is significantly changed. Also, ASAT configurations experience little to no modifications over time.

Many of the mentioned studies share common views and purposes with our study and TEDIOUS. However, as far as we know, our work stands out because TEDIOUS is the first approach that attempts to predict technical debts at method-level with a wide variety of easy to use and extract information.

## CHAPTER 3 THE APPROACH AND STUDY DEFINITION

### 3.1 The Approach

This section will describe the steps followed to design TEDIIOUS, our proposed machine learning detector to identify design technical debts to self-admit. It will also define its characteristics, how it works and how to use it. TEDIIOUS works at method-level since it is typically the granularity at which developers introduce SATD, as proven by da S. Maldonado and Shihab (2015) and Potdar and Shihab (2014). In other terms, it is able to define whether a method contains a design technical debt or not. Class-level granularity would be too coarse because technical debts normally admitted by developers are related to specific and punctual issues in the source code. Additionally, a class could contain a TD but it would be impossible to precisely identify the source of the problem since a class contains several methods and LOC.

TEDIIOUS works as shown in Figure 3.1. Two datasets are required as inputs: the training set and the test set. The training set contains labeled data, which has source code from a project where technical debts are known and have been self-admitted through comments. The test set contains unlabeled data, which can be any source code under development or already released where TEDIIOUS can attempt to recommend where TD should be self-admitted or where source code should be improved.

For the training set, various kinds of metrics and static analysis warnings are extracted from the source code as well as SATD methods in order to build an oracle to train the model. These labeled SATD methods are essential for the machine learner since supervised learning is performed, meaning each method is labeled as true or false. It is true when the method is a TD and false if it is not.

Once all the information is extracted, feature preprocessing and selection is applied. Multi-collinearity, a phenomenon occurring when two predictor variables are highly correlated, meaning that one can be linearly predicted by the other, is dealt with. Feature selection is applied to retain only the most relevant variables to train the predictor. Finally, re-balancing is performed to address the issue of the low amount of positive examples, *i.e.* SATD methods. With the preprocessed features and the oracle now defined (each method is labeled as SATD or not), the machine learners can be trained.

In parallel, the test set is also being prepared. The same features are extracted from the source code but no SATD matching is required since the data is unlabeled. SATD are only required for the oracle, which is used for training the models. A similar feature filtering is

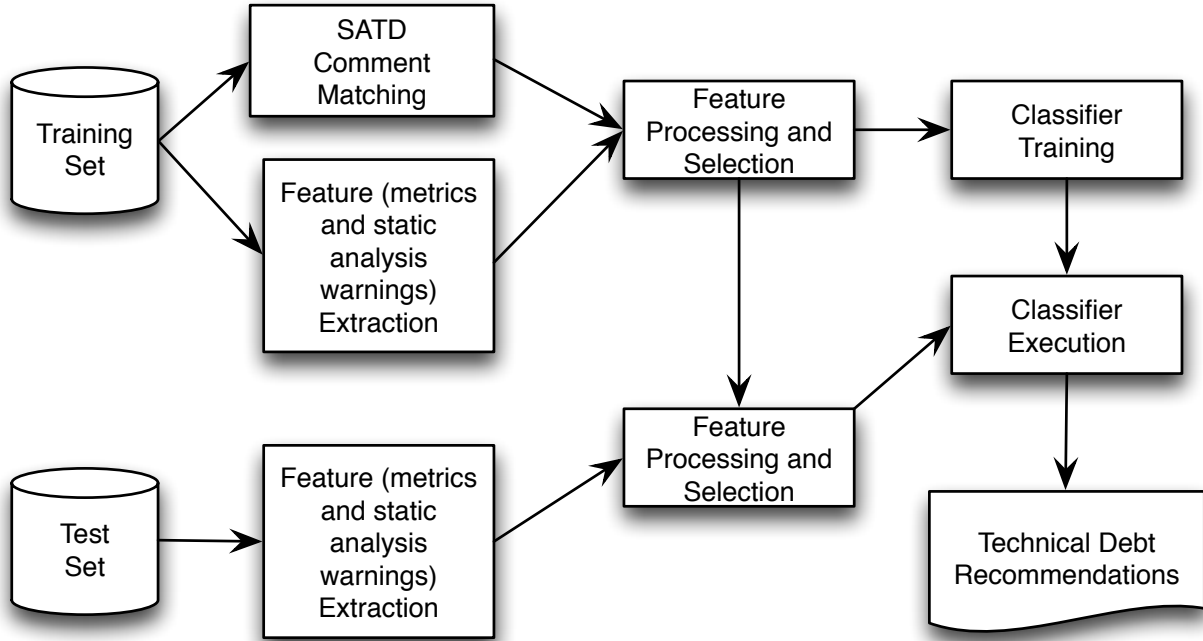


Figure 3.1 Proposed approach for recommending SATD with TEDIOUS.

applied, except for the re-balancing since it is only required on the labeled data. With both the test set and the previously trained classifier, predictions can be made on the test set in order to recommend when to self-admit technical debts.

Each step of the process will be described in the following sections. Firstly, the features used in more details: source code metrics and warnings raised by static analysis tools. Secondly, the method employed to identify SATD. Thirdly, the feature preprocessing: multi-collinearity, feature selection and re-balancing. Finally, the training and application of the machine learning models.

### 3.1.1 Features

Three pieces of information extracted from the source code are necessary to accurately describe the source code: structural metrics, readability metrics and warnings raised by static analysis tools. There are reasons these specific characteristics were retained to describe the source code. The structural metrics are essential to capture symptoms of complex, heavily coupled and poorly designed code. These metrics explain the quality of the implementation and the software's design. The readability metrics quantify symptoms of poorly documented code or hard to read and understand. Warnings from static analysis tools are related to



more specific bad choices rather than globally bad code. They are issues which could lead to low maintainability and understandability of the code or which could potentially introduce defects in the future. In the following sections, these metrics and warnings are described more in depth.

## Source Code Metrics

Source code metrics are extracted to characterize its size, coupling, complexity and number of comments for readability. Nine source code metrics are used. To define the size, metrics like LOC or number of statements are calculated. For coupling, a metric such as number of call sites is computed. For complexity, McCabe cyclomatic complexity (McCabe, 1990a), number of defined variables, number of expressions and number of identifiers are calculated. It is important to know that not all comments are considered. SATD related comments are ignored in the empirical evaluation to avoid TEDIOUS becoming a self-prophecy. This issue will be covered later in the study design.

Firstly, to extract those source code metrics, an XML representation of the Java source code was generated using the srcML tool (Collard et al., 2003) and metrics' computation was applied to it. **SHOW IMAGE OF XML REPRESENTATION. SHOW IMAGE OF PSEUDOCODE AND EXPLAIN IT. VOIR PDF DU COURRIEL DANS DROPBOX. CODE DE GIULIO.** It was also required to link comments to their related methods. The rule used was that any comments directly preceding or inside a method was assigned to it, rather it be a block of comments or just a single line. This step is essential to be able to classify which method is a SATD and which one is not. Some methods were excluded from our analysis because they did not fit the context of our study, namely getter and setter methods since they are irrelevant with design debts. To do so, we looked for method prefixes matching *get* or *set* and made up from at least a single line of code. When these two criteria were covered, the method was removed from the dataset.

Secondly, to extract the code readability metric, we use the one proposed by Buse and Weimer (2010) and its related tool, based on a machine learning approach. This metric is based on specific characteristics of the source code: indentation, line length, identifier length, comment density, and the use of keywords and operators. The tool was also designed using feedback from human annotators, they were asked to rate the readability of code snippets, that was then used to classify snippets as "less" or "more" readable. A value between 0 and 1 is then computed based on these characteristics, 1 being the highest readability. The readability metric was considered relevant because, as mentioned by Bavota and Russo (2016), code readability is strongly correlated with the introduction of technical debts. Code that

is difficult to read is consequently difficult to maintain and understand (Buse and Weimer, 2010) thus more likely to contain TD. Finally, here are the nine source-code metrics we extracted:

- *LOC*: Number of lines of code in the body of a method.
- *Number of statements*: Number of occurrences of expression statements in a method. In case of local class definitions, the number of statements in the enclosing method is increased by the total number of statements of the local class.
- *Number of comments*: Number of single-line and multi-line comments in a method.
- *McCabe cyclomatic complexity*: Number of linearly independent paths of a method (McCabe, 1990b).
- *Number of passed parameters*: Number of parameters of a method.
- *Number of identifiers*: Number of unique identifiers in a method.
- *Number of call sites*: Number of locations in the code where zero or more arguments are passed to a method, or zero or more return values are received from the method.
- *Number of declarations*: Number of variable and class declaration in a method.
- *Number of expressions*: Number of expressions contained in a method.

## Warnings Raised by Static Analysis Tools

Warnings raised by static analysis tools are essential to detect poor coding practices, which are also related to the introduction of technical debts. We cannot directly relate a single flagged practice to a TD. However, we can wonder if several flags are justifiable or not, and if they can be caused by the presence of a TD in the source code. Having this hypothesis in mind, we used two popular static analysis tools, namely CheckStyle and PMD. Firstly, CheckStyle (che) is widely used to check the adherence to coding standards and pieces of code that are potentially smells. It performs its analysis based on a configuration file, which can be modified at the discretion of the users. For our study, the default configuration containing code styles defined by Oracle and 43 checks was used. PMD (pmd) main goal is to find common programming flaws such as unused objects, unnecessary catch blocks or incomprehensible naming. Similarly to CheckStyle, the default configuration was used, which contains 168 checks. Several reasons explains the choice of these two static analysis tools:

they are adopted by OSS (Beller et al., 2016), they provide a wide range of warnings related to code styles and programming practices and they can be executed on source code statically. It is important to know that SATD comments were removed when performing the analysis.

### 3.1.2 Identification of Self-Admitted Technical Debt

As mentioned previously, the purpose of this study is not to propose a novel approach to detect SATD using information from comments. Previous work has been completed aiming to address this issue by using matching (da S. Maldonado and Shihab, 2015), (Potdar and Shihab, 2014) or NLP combined with machine learners (Maldonado et al., 2017b). However, we still needed a dataset with methods tagged as design debt to train our machine learning models. Maldonado et al. (2017b), which worked on the NLP approach, published a dataset of 10 open source projects annotated with methods tagged as technical debt or not. We used this dataset for our machine learning models and only the design debts were retained.

Some preprocessing had to be done on the dataset since it reported SATD at file-level and not method-level. To link SATD to methods, we matched the SATD comment string to the comments attached to methods. We used pattern matching in order to achieve this result, making sure that method comment strings completely matched SATD comments before tagging it as a technical debt.

### 3.1.3 Feature Preprocessing

Several characteristics have been extracted from the source code, however, not all of them are relevant or necessary to train our models. Some clean up have to be done to reduce the size of the data input and improve the training phase. Multi-collinearity have to be dealt with, feature selection as to be applied as well as training set re-balancing. **SHOW IMAGE OF PSEUDOCODE AND EXPLAIN IT. FAIRE UN GRAPH STYLE LE PROCESS AU COMPLET. UN CARRE = UNE SOUS SECTION.**

#### Multi-Collinearity

We computed a lot features to characterize the source code of the projects, however, some of them can be strongly correlated and vary in the same way. Keeping these pairs of features would cause redundancy since they can be mutually linearly predicted. That is why, when facing a duo of such features, we only keep the one that better correlates with the dependent variable, the SATD methods. The *varclus* function in R, from the *Hmisc* package, was used to help us achieve this preprocessing. This function performs a hierarchical cluster analysis

of features to detect when two variable are positive based on similarity measures. It is mainly used to assess collinearity and redundancy, consequently resulting in data reduction. Hoeffding D statistic, squared Pearson or Spearman correlations measures can be applied. In this study, the Spearman’s  $\rho$  rank correlation measure was retained. To identify the problematic duos, the cluster tree has to be cut at a particular level of  $\rho^2$ , which represents the correlation value. In our case, a value of  $\rho^2 = 0.64$  was used since it corresponds to a strong correlation (Cohen, 1988).

## Feature Selection and Normalization

Some features will vary a lot or not at all between methods. These features are not useful to build a predictor because they can’t be used as proper learning variables, they won’t be determinant compared to all the other features. The process of selecting only a relevant subset of all possible features is called feature selection. Several reasons can justify going through this selection: improving the prediction performance of machine learning models, improve the speed and cost-effectiveness of predictors, and simplify the models to better understand and interpret the underlying process behind the dataset generation (Guyon and Elisseeff, 2003).

The *RemoveUseless* filter implemented in Weka (Hall et al., 2009) was used to perform feature selection. It looks for features that never vary or features that vary too much. For the latter, it looked for features that had a percentage of variance above a specific treshold, which was set to 99%.

In addition to feature selection, the metrics were also normalized. Several projects were analyzed, all having significant differences in complexity and size characteristics. Those aspects of the dataset will be covered in the study definition section. This normalization is necessary to reduce the effect of those differences on the predictor’s training and to achieve good cross-project prediction performance.

## Re-Balancing

To build performing predictors, a quality training set must be fed to the machine learner. One important aspect is to have a balanced dataset, which means having as much as possible an equal number of positive and negative examples, in our context, as many SATD tagged methods as clean methods. This is a serious problem in our dataset since the vast majority of methods are not technical debts (this will be discussed more in depth in the next section), only a minority contain SATD. There are two ways to address this issue: under-sample the

majority class (methods with no SATD) or over-sample the minority class (SATD tagged methods). Since the training set is so highly unbalanced, the number of instances of the minority class is excessively small, the second option was favored. In fact, under-sampling would result in a very small training set. To apply over-sampling, artificial instances of SATD methods must be generated from the existing ones. To do so, Weka provides a tool to perform over-sampling, called Synthetic Minority Over-sampling Technique (SMOTE) (Chawla et al., 2002), which combines under-sampling the majority class and over-sampling the minority class to achieve improved classifier performance.

### 3.1.4 Building and Applying Machine Learning Models

We extracted various metrics, we identified SATD methods and we performed a preprocessing on features, the only remaining step is building and applying the machine learning models. Two sets are required: the training set and testing set. The training set contains the methods with their corresponding features and an additional variable to tag them as positive or negative (SATD or not). It is used to build the models. The testing set contains the same methods with the corresponding features, but not the variable tagging the methods because we want to test the prediction performance from a blank dataset. We experimented with five types of machine learners in Weka (Hall et al., 2009): Decision Trees (J48), Bayesian classifiers, Random Forests, Random Trees, and Bagging with Decision Trees. Only the default configurations were used, however, further work could be made by trying to optimize these configurations. Here is a little overview of each algorithms:

- *Decision trees*, namely J48, which implements the standard C4.5 algorithm using the concept of information entropy (Quinlan, 1993).
- *Bayesian classifiers*, which apply the Bayes' theorem to classify observations, assuming strong independence between features. More specifically, we use BayesNet in Weka, which is the base class for Bayes Network classifiers. It provides datastructures and facilities common to learning algorithms K2 and B.
- *Random forests*, which averages multiple decision trees trained on different parts of a same training set, with the aim to reduce the variance of the classifications and the risk of overfitting to the training set (Breiman, 2001).
- *Random trees*, which build decision trees considering a number of randomly chosen attributes at each node.

- *Bagging*, which combines multiple classifiers (decision trees in our case) built on random samples of the training set (Breiman, 1996). It was designed to improve the stability and accuracy of machine learning algorithms, to reduce the variance and to avoid overfitting.

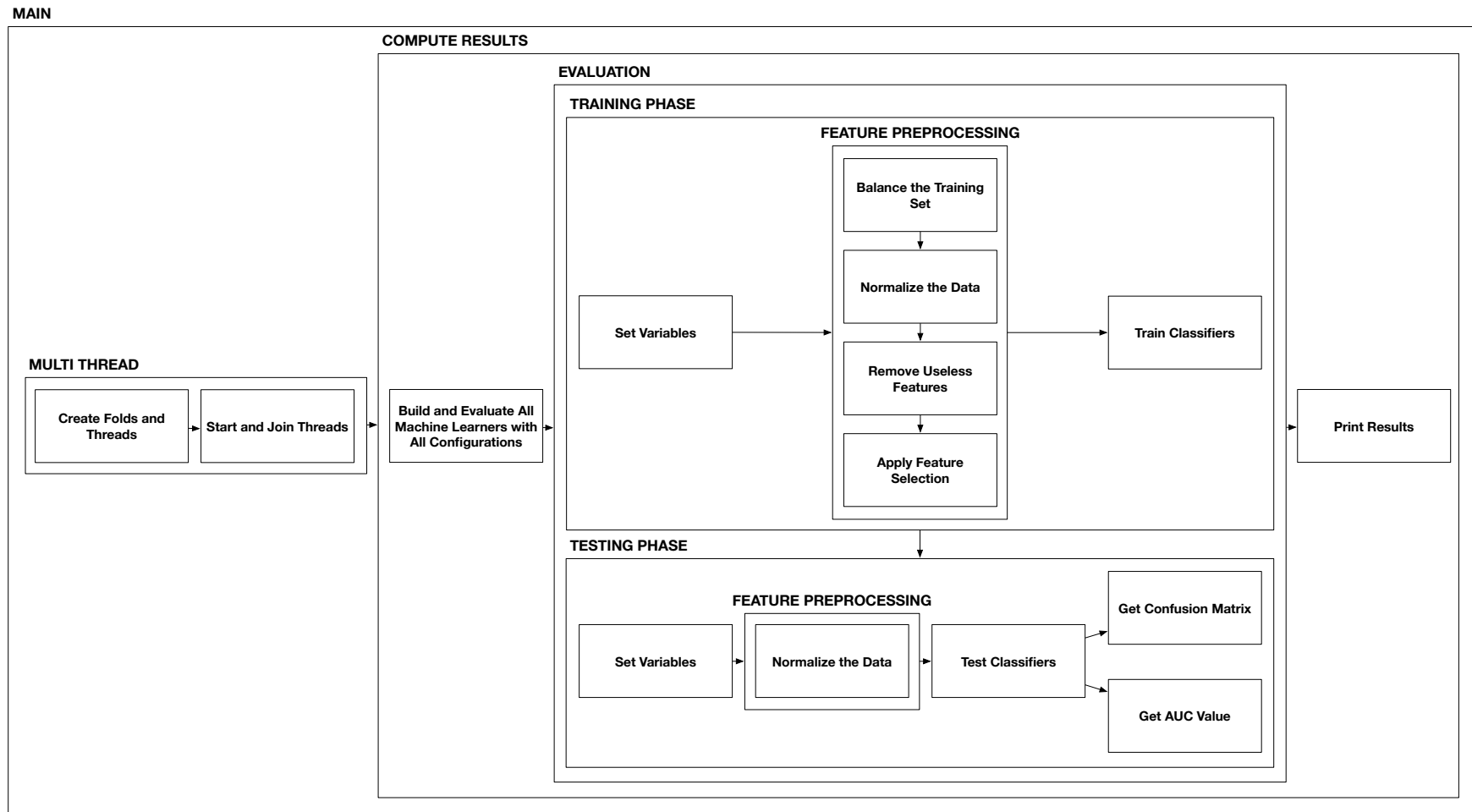


Figure 3.2 Process for building and applying machine learners.

Figure 3.2 provides an overview of the machine learning process. To increase its speed, several threads are created. For the 10 fold cross-validation inter-project analysis, one thread is started for each fold, which were generated beforehand for each software system. The following actions are performed simultaneously on each thread and the computation is finished once each of them are finished. All possible combinations of machine learners and configurations are trained and tested on each fold. We have 5 different types of machine learners, the possibility of balancing the training set or not, and the possibility of applying feature selection or not, for a total of 20 predictors.

The evaluation step consists of a training and testing phase. In the training phase, the variables to predict are set, *i.e.* SATD methods, and feature preprocessing is applied. The training set can be balanced or not, data is normalized, useless features are removed and feature selection is applied or not. The models can then be trained. In the testing phase, the variables to predict are set again, as for the feature preprocessing, only data normalization is performed. The classifiers are tested and then the confusion matrix and the AUC value computed. Results are finally printed to perform further analysis.

## 3.2 Study Definition

The goal of this study is to assess the prediction performance of our machine learning based approach in recommending technical debts to self-admit. The focus of this study is to enhance source code quality, more specifically its maintainability and understandability, by keeping track of technical debts which can be corrected in the future. The perspective of this study is to be able to suggest to developers when to admit technical debts. We aim at addressing three research questions:

- **RQ1:** How does TEDIOUS work for recommending SATD within-project?
- **RQ2:** How does TEDIOUS work for recommending SATD across-project?
- **RQ3:** How would a method-level smell detector compare with TEDIOUS?

### 3.2.1 Dataset



Table 3.1 Characteristics of the studied projects.

Project	Release	Number of				Number of Comments ∈ Methods	Number of Design SATD		% of Methods with design SATD
		Files	Classes	Methods	Comments		∉ Methods	∈ Methods	
Ant	1.7.0	1,113	1,575	11,052	20,325	13,359	1	57	0.5%
ArgoUML	0.34	1,922	2,579	14,346	64,393	17,722	203	425	2%
Columba	1.4	1,549	1,884	7,035	33,415	10,305	8	418	5%
Hibernate	3.3.2 GA	2,129	2,529	17,405	15,901	9,073	21	377	2%
jEdit	4.2	394	889	4,785	15,468	10,894	6	77	2%
jFreeChart	1.0.19	1,017	1,091	10,343	22,827	15,412	4	1,881	18%
jMeter	2.1	1,048	1,328	8,680	19,721	12,672	95	424	5%
jRuby	1.4.0	970	2,063	14,163	10,599	7,809	16	275	2%
Squirrel	3.0.3	2,325	4,123	16,648	25,216	15,574	35	173	1%

To evaluate our approach, we used a dataset that was already analyzed to find SATD methods (Maldonado et al., 2017b). It consists of ten open source projects, although we used only nine of them since we could not download the specific version of EMF, where SATD were detected using a NLP approach. The methods were then manually validated and classified. Table 5.1 summarizes the characteristics of all studied projects. It provides information on project releases; number of files, classes, methods and comments in projects; number of comments in methods; number of design SATD in methods and not in methods; and percentage of methods with design SATD.

Some differences were observed with the characteristics extracted from the original paper (Maldonado et al., 2017b), concerning the number of classes, methods and comments. Several reasons can explain these disparities: different extraction tooling, tools characteristics and processing. For example, we considered each comment as a single entity, whereas Maldonado et al. (2017b) regrouped successive line comments. Additionally, we did not establish a separation between classes and their inner classes, and we considered interfaces as classes. Methods related to inner classes were associated to its container. However, these differences are not an issue for our study since they concern classes and our approach is method-level based. Some files from Maldonado et al. (2017b) analysis could have been left aside because of their absence of comments.

We can obtain some interesting information when looking at Table 5.1. As explained previously, we clearly see a prevalence of method-related SATD compared to class-level SATD. They are at least 2 times more common for ARGOUML, which contains about half of all the class-level TD in the dataset, and can be up to 470 times more common for JFREECHART, only 4 out of the 1,885 design SATD are at class-level. Globally, we are around 10 times more likely to encounter a method-level design technical debt in our dataset than class-level. We also observe that the dataset is highly unbalanced between SATD prone and non SATD prone methods. JFREECHART provides a decent ratio with 18% of methods containing a design TD but all other projects have 5% or less of their methods containing design debts. To put this into perspective, out of the 11,052 methods in ANT, only 57 are SATD prone. For JEDIT, only 77 instances out of 4,785 are prone to contain a SATD. Unsurprisingly, as we will discuss in the analysis of study results, these two projects achieved the lowest performance values.

The replication package provided by Maldonado et al. (2017b) contains information on SATD at class-level. However, to build the oracle, we need to assign SATD at method-level. To do so, we performed pattern matching between known SATD comments and comments attached to methods. If a comment is matched inside a class but not a method, it is attached

to the class, if it is matched outside of a class, it is attached to the file. These class-level and file-level technical debts are not considered in our study, which is not a big issue since they represent the minority.

### 3.2.2 Analysis Method

For **RQ1**, we want to know how TEDIOUS work for recommending SATD within-project. A 10-fold cross validation was performed on each project. In other terms, the dataset of a single project is divided into 10 folds, the machine learner is trained on 9 of them and tested on the remaining one, until all 10 configurations are processed to limit the effect of randomness. The performance values are averaged over the 10 iterations to obtain the most representative picture. For **RQ2**, we want to know how our approach work for recommending SATD across-project. The process is similar to **RQ1**, but instead we train on 8 projects and test on the remaining one, until all the 9 possible combinations are executed.

Standard performance metrics for evaluating automated classification were computed to analyze our approach: precision, recall and  $F_1$  score. These metrics were computed for the SATD category.

Precision (Pr) is the percentage of relevant instances of methods predicted as SATD among all retrieved instances. TP and FP are the number of true positives, correct methods predicted as SATD, and false positives, incorrect methods predicted as SATD.

$$Pr = \frac{TP}{TP + FP}$$

Recall (Rc) is the percentage of relevant instances of SATD methods that have been retrieved over all relevant instances. FN is the number of false negatives, incorrect methods predicted as non SATD.

$$Rc = \frac{TP}{TP + FN}$$

The  $F_1$  score is the harmonic mean between precision and recall, which provides a single measurement for evaluating a system.

$$F_1 = 2 \cdot \frac{PR \cdot RC}{PR + RC}$$

The previous metrics are specific to the SATD class, which means true negatives TN, correct methods predicted as non SATD, are not considered. Consequently, other metrics

are required to complement the analysis: accuracy, Matthews Correlation Coefficient (MCC) (Matthews, 1975), and the Area under the Receiving Operating Characteristics (ROC) Curve (AUC).

Accuracy (Acc) is the total number of methods correctly predicted, whether it is containing a SATD or not, among all the methods analyzed.

$$Acc = \frac{TP + TN}{TP + TN + FP + FN}$$

The MCC is a metric used in machine learning to evaluate the quality of a two-class classifier. It is especially useful when the dataset is unbalanced (Matthews, 1975). Values vary between -1 for a completely wrong classifier and 1 for a completely correct classifier.

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

The ROC curve is created by plotting the true positive rate against the false positive rate at various classifier thresholds. The AUC is the area under the ROC curve, it provides a value to evaluate the quality of the classifier. A value of AUC=0.5 refers to a random classifier and the higher the value, the better the classifier.

To have a good idea of the performance of each machine learner, each of the previous metrics have to be considered in the evaluation. We want a balance between precision and recall because we want as much as possible to detect real technical debts and all of them. We cannot only use  $F_1$  score because we want to take into account the effect of chance on the predictions. That's why we also computed the MCC and AUC values.

In addition to these performance indicators, we also consider the importance of each features for the training of the predictors. We used a technique implemented in Weka for Random Forests named Mean Decrease Impurity (MDI) (Louppe et al., 2013), which measures the importance of variables on randomized decision trees.

For **RQ3**, we want to compare TEDIOUS with a popular method-level smell detector (DECOR) (Moha et al., 2010) in classifying as technical debt methods labeled as SATD. DECOR can detect a large amount of smells, but most of them are at class-level, which are not relevant with the level at which TEDIOUS work. Instead of using all of them, we narrowed our analysis on two method-level smells, *Long Method* and *Long Parameter List*. To identify a Long Method smell, DECOR follows the rule  $LOC > th_1$  where  $> th_1$  is a threshold for the LOC. To identify a Long Parameter List smell, DECOR follows the rule  $ParNbr > th_2$

where  $ParNbr > th_2$  is a threshold for the number of parameters. Various thresholds for LOC and ParNbr were considered in our study, between percentile 0.5 and 0.95, as well as the default thresholds, namely percentile 0.75 for LOC and outlier (third quartile  $+1.5 \cdot IQR$  (interquartile range)) for ParNbr.

To finish, we performed a qualitative analysis on false positives and false negatives examples we obtained when evaluating our predictors. Its purpose is to complement our quantitative analysis and discuss the limitations of our approach in recommending TD with real examples.

## CHAPTER 4 ANALYSIS OF STUDY RESULTS AND THREATS TO VALIDITY

### 4.1 Study Results

This section reports the study results in the context of each research question. Tables provide visual representation and summarize the main results. More in depth analysis is discussed for the three research questions and the qualitative analysis.

#### 4.1.1 How does TEDIOUS work for recommending SATD within-project?

Table 4.1 presents the average performance results of a 10-fold cross validation within-project executed 10 times and on different machine learners. The average was computed for the 9 studied projects. The 10-fold cross validation was performed with balancing using SMOTE and without balancing.

On the unbalanced dataset, the best classifier is the one using the Random Forests algorithm. It achieves the best balance between precision (49.97%) and recall (52.19%), obtaining a  $F_1$  score of 47.15%, the highest of all machine learners. We also notice that the Bagging algorithm is performing almost as well as Random Forests, even obtaining a slightly better precision but a weaker  $F_1$  score. The accuracy of Random Forests, which includes the correct classification of negatives (the vast majority of the data), is 93.32% and almost all the other machine learners obtain an accuracy higher than 90%, between [89.01% – 93.35%]. MCC is on average  $> 0.4$ , which is translated into a moderate correlation, and AUC is  $> 0.9$  (close to a perfect classifier) for Random Forests, Bagging and Bayesian and  $> 0.7$  for j48 and Random Trees.

On the balanced dataset, the best classifier is still Random Forests, with a precision of 26.56%, recall of 68.26% and  $F_1$  score of 36.04%. Its MCC value is the highest at 0.37, moderate correlation, and the same goes for its AUC value which is the same as previously, 0.92. The purpose of balancing is achieved since the recall of each machine learners is higher than previously, at the expense of precision. There is a clear gap between the Bayesian classifier and the others, it is definitely performing more poorly. All the performance values are the worst, except for the recall which is really good but not enough to compensate. In fact, it performs like a random classifier if we look at the MCC value which is almost 0. The other classifiers all performed similarly, having a precision between [16.03% – 18.40%], a recall between [63.22% – 75.12%] and a  $F_1$  score around 25%. Their MCC value is around 0.3,

Table 4.1 Average performance of different machine learners for within-project prediction.

<b>Without Balancing</b>						
<b>ML</b>	<b>Pr</b>	<b>Rc</b>	<b>F<sub>1</sub></b>	<b>Acc</b>	<b>MCC</b>	<b>AUC</b>
<b>Random Forests</b>	49.97	52.19	47.15	93.32	0.47	0.92
<b>Bagging</b>	51.91	48.45	45.97	93.35	0.45	0.92
<b>Bayesian</b>	24.29	78.77	34.18	89.01	0.38	0.93
<b>j48</b>	34.86	54.42	39.54	94.18	0.39	0.82
<b>Random Trees</b>	23.09	52.49	29.96	90.35	0.30	0.73
<b>With Balancing</b>						
<b>ML</b>	<b>Pr</b>	<b>Rc</b>	<b>F<sub>1</sub></b>	<b>Acc</b>	<b>MCC</b>	<b>AUC</b>
<b>Random Forests</b>	26.56	68.26	36.04	90.45	0.37	0.92
<b>Bagging</b>	18.4	75.12	28.24	85.58	0.31	0.90
<b>Bayesian</b>	4.00	94.07	7.55	15.66	0.04	0.72
<b>j48</b>	16.95	77.76	26.45	84.04	0.30	0.85
<b>Random Trees</b>	16.03	63.22	24.49	85.34	0.26	0.75

which translates to a fair correlation and the AUC value is decent at 0.7 or more. However, the results are globally weaker with balancing than without it.

Table 4.2 highlights the within-project prediction results, for each system, using Random Forests, and using balancing or not. Random Forests only was used since it is best classifier based on Table 4.1. If we look at the unbalanced dataset, two systems are performing way worse than the others, namely ANT and JEDIT. There is a reason behind this if we look back at Table 3.1. The projects, other than JFREECHART with 18%, all have a percentage of their methods containing SATD below or equal to 5%. ANT only has 0.5% of its methods containing SATD and JEDIT 2%. This explains the low performance values of ANT (precision 0.91%, recall 16.39% and  $F_1$  score 1.73%) and JEDIT (precision 5.24%, recall 25.71% and  $F_1$  score 8.71%). The AUC values are still decent, respectively with 0.77 and 0.81, but the MCC values, respectively with 0 and 0.06, clearly prove us that the classifier is as good as a random one.

JFREECHART is the project containing the most number of SATD and is consequently the project where the classifier performs the best. It obtains high precision and recall (84.58% and 82.52%) as well as high MCC and AUC (0.83 and 0.99). Performance values on the other 6 projects are also promising, the  $F_1$  score is almost always  $> 50\%$ , the MCC is between  $[0.47 - 0.64]$  which is moderate to strong correlation, and the AUC is in the interval

Table 4.2 Within-project prediction: results of Random Forests for each system, without and with SMOTE balancing.

<b>Without Balancing</b>						
<b>System</b>	<b>Pr</b>	<b>Rc</b>	<b>F<sub>1</sub></b>	<b>Acc</b>	<b>MCC</b>	<b>AUC</b>
Ant	0.91	16.39	1.73	84.59	0.00	0.77
ArgoUML	85.19	38.10	52.65	93.25	0.54	0.91
Columba	36.40	65.94	46.91	96.02	0.47	0.94
Hibernate	53.44	65.22	58.74	96.80	0.57	0.97
jEdit	5.24	25.71	8.71	85.51	0.06	0.81
jFreeChart	84.58	82.52	83.54	98.91	0.83	0.99
jMeter	53.38	47.37	52.30	96.69	0.51	0.94
jRuby	52.27	84.02	64.45	94.21	0.64	0.97
Squirrel	73.33	44.44	55.35	99.51	0.57	0.97
<b>With Balancing</b>						
<b>System</b>	<b>Pr</b>	<b>Rc</b>	<b>F<sub>1</sub></b>	<b>Acc</b>	<b>MCC</b>	<b>AUC</b>
Ant	2.46	44.26	4.67	85.02	0.08	0.83
ArgoUML	47.03	65.39	54.71	89.34	0.50	0.90
Columba	15.35	74.64	25.46	88.35	0.30	0.94
Hibernate	19.85	89.13	32.47	87.04	0.38	0.95
jEdit	7.74	34.29	12.63	87.25	0.11	0.86
jFreeChart	62.98	92.68	75.00	97.94	0.75	0.99
jMeter	32.03	64.47	42.79	93.40	0.42	0.92
jRuby	32.75	91.91	48.29	87.72	0.50	0.92
Squirrel	18.81	57.58	28.36	98.02	0.32	0.96

[0.91 – 0.97]. We notice that the prediction performance of TEDIOUS is dependent on the system and not only the number of SATD it is trained on. SQUIRREL has a slightly higher percentage of SATD methods than ANT and slightly lower than JEDIT, but it still performs significantly better than these two projects (73.33% precision and 44.44% recall).

If we look at the balanced dataset, the same trend is observed as in the balanced dataset but with lower performance results. Precision is generally lower except for ANT and JEDIT which obtain a small improvement. These two systems should normally benefit from balancing but the data from the few SATDs is not even enough to build a decent artificial training set, leading to a negligible gain in precision. However, as expected with balancing, we see a decent increase in their recall and the same goes for the other systems. Generally speaking, the accuracy,  $F_1$  score, MCC and AUC is better for ANT and JEDIT only, the other



systems did not benefit from the balancing.

Table 4.3 Top 10 discriminant features (within-project prediction). (M): source code metrics, (CS): CheckStyle checks, (P): PMD checks.

Metric Name	Ant	ArgoUML	Columba	Hibernate	jEdit	jFreeChart	jMeter	jRuby	Squirrel
Readability (R)	5	1	2	1	1	1	1	1	1
LOC (M)	2	2	5	2	2	3	2	3	4
DeclNbr (M)	4	3	7	4	3	4	3	4	3
ParNbr (M)	8	5	9	7	7	7	7	7	7
ExprStmtNbr (M)	6	4	—	5	4	5	5	5	5
McCabe (M)	10	7	—	6	6	6	6	6	6
CommentNbr (M)	—	6	—	3	5	2	4	2	2
LineLength (CS)	—	—	—	9	—	—	9	8	9
LocalVariableCouldBeFinal (P)	—	—	—	10	9	—	—	9	10
DataflowAnomalyAnalysis (P)	—	10	—	—	10	—	—	—	—
FinalParameters (CS)	—	—	—	—	—	8	8	—	—
MissingSwitchDefault (CS)	—	8	4	—	—	—	—	—	—
AvoidReassigningParameters (P)	7	—	—	—	—	—	—	—	—
CollapsibleIfStatements (P)	9	—	—	—	—	—	—	—	—
EmptyIfStmt (P)	—	—	8	—	—	—	—	—	—
IfStmtsMustUseBraces (P)	—	—	—	—	8	—	—	—	—
LeftCurly (CS)	—	—	—	—	—	—	—	—	8
LocalVariableName (CS)	—	—	1	—	—	—	—	—	—
MethodArgumentCouldBeFinal (P)	—	—	—	—	—	—	—	10	—
MethodLength (CS)	—	—	—	—	—	—	10	—	—
OptimizableToArrayCall (P)	—	—	10	—	—	—	—	—	—
ParameterNumber (CS)	—	—	—	—	—	10	—	—	—
ParenPad (CS)	—	—	—	8	—	—	—	—	—
ShortVariable (P)	—	—	—	—	—	9	—	—	—
SimplifyBooleanReturns (CS)	—	9	—	—	—	—	—	—	—
SwitchStmtsShouldHaveDefault (P)	—	—	6	—	—	—	—	—	—
UselessParentheses (P)	3	—	—	—	—	—	—	—	—
UseLocaleWithCaseConversions (P)	—	—	3	—	—	—	—	—	—
UseStringBufferForStringAppends (P)	1	—	—	—	—	—	—	—	—

Table 4.3 reports the top 10 features in within-project prediction according to the MDI technique. The importance of each feature is ranked for each system. Four features are in the top 10 of all projects, and they are all source code metrics. The most important one is the readability metric of Buse and Weimer (2008), which is number the top feature for 7 systems. This observation is contrasting with the work of Bavota and Russo (2016) where they found that there was little correlation between SATD and code quality metrics as well as readability. The difference may lie in the fact that TEDIOUS works at method-level and not class-level like in the study of Bavota and Russo (2016). A class contains several methods, some can be readable and others not really. The previous work may not have been able to work at granularity fine enough to detect these potential SATDs. The other three features are the number of declarations (*DeclNbr*), of parameters (*ParNbr*) and the number of lines of code (*LOC*). Having *ParNbr* and *LOC* in the top features is interesting because they are typical metrics used in smell detectors. In fact, for **RQ<sub>3</sub>**, we study how a smell detector compares with TEDIOUS by relying solely on *Long Method* and *Long Parameter List* smell detection.

Other important features, which appears in the top 10 of over half the systems, are the number of expressions (*ExprStmtNbr*), the McCabe cyclomatic complexity (*McCabe*) and the number of comments (*CommentNbr*). For *CommentNbr*, the SATD comments were excluded in order to keep the prediction unbiased. All these metrics are also from the source code.

The other features are all warning checks from CheckStyle and PMD. The length of lines (*LineLength*) and *LocalVariableCouldBeFinal* warnings are the most common, with the others being for more specific systems. Most of these features relate to poorly written code. For example, *LineLength* checks for long lines, which are hard to read in printouts or if the coding screen space is limited. *LocalVariableCouldBeFinal* refers to a variable that is assigned only once. *LocalVariableName* is the most important feature for COLUMBA and it checks for single-character variables or local variables with same name in different scopes. *UseStringBufferForStringAppends* is the most important feature in ANT and it checks if the is a non-trivial number of the operator `+=` for appending strings in the source code. For further details on the meaning of each warning, you can refer to the documentation of CheckStyle<sup>1</sup> and PMD<sup>2</sup>.

We notice that two Checkstyle warnings, *ParameterNumber* and *MethodLength*, are very similar to two source code metrics, namely *ParNbr* and *LOC*. Intuitively, they should have been removed by the Spearman’s analysis since they seem strongly correlated to the source

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<sup>1</sup><http://checkstyle.sourceforge.net/checks.html>

<sup>2</sup><https://pmd.github.io/pmd-5.5.5/pmd-java/rules/index.html>

code metrics. However, differently from the metrics, the warnings are boolean features. CheckStyle looks if there are over 7 parameters for *ParameterNumber* and over 150 LOC for *LOC*, returning *TRUE* or *FALSE* accordingly. This is why these warnings were not removed by Spearman’s analysis.

**RQ<sub>1</sub> summary:** Random Forests classifiers achieve the best average performance for within-project prediction of design technical debts to recommend. Precision of 49.97%, recall of 52.19% and  $F_1$  score of 47.15% are achieved for an unbalanced dataset. When using Random Forests on each system, high MCC and AUC values indicate healthy classifiers except for the ones with a small number of SATD instances. Balancing does improve recall but it does not result in better classifiers because of a substantial decrease in precision. Code readability, complexity and size are the most useful features in building the predictors, for all systems, in addition to some system-specific analysis checks.

#### 4.1.2 How does TEDIOUS work for recommending SATD across-project?

Table 4.4 highlights the average performance of different machine learners for cross-project prediction. The process is similar to **RQ2**, instead of performing a cross-validation on each system individually, the classifier is trained on 8 systems and tested on 1 system. The classifiers are trained with a balanced dataset (top section of the table) and with an unbalanced one (bottom section). The same trend is observed for the within-project and cross-project prediction: Random Forests outperforms the other machine learners and rebalancing does not provide a significant payoff.

On the unbalanced dataset, the best classifier is the one using the Random Forests algorithm. It achieves the best precision (67.22%), a good recall (54.89%), and the best  $F_1$  score of 55.43%. Compared to the within-project results, the improvement in precision is +17.25%, in recall +2.70% and in  $F_1$  score is +8.28%. For the other machine learners, the precision varies between [48.31% – 58.85%] and the recall between [51.62% – 64.25%]. MCC is always  $> 0.4$  (moderate correlation) and  $AUC > 0.7$ .

On the balanced dataset, the best classifier is still Random Forests, with a precision of 47.49%, recall of 78.75% and  $F_1$  score of 56.45%. The  $F_1$  score is slightly better than without balancing, but as expected precision suffers a large loss in order to obtain higher recall. We also notice that MCC and AUC values are slightly lower than without balancing. A similar trend is observed for the other machine learners, with Bayesian suffering the most from rebalancing, performing almost like a random classifier (MCC near 0). It is important to notice that, other than Random Forests, none of the other algorithms obtain a higher  $F_1$  score.

Table 4.4 Average performance of different machine learners for cross-project prediction.

<b>Without Balancing</b>						
<b>ML</b>	<b>Pr</b>	<b>Rc</b>	<b><math>F_1</math></b>	<b>Acc</b>	<b>MCC</b>	<b>AUC</b>
<b>Random Forests</b>	67.22	54.89	55.43	91.89	0.55	0.91
<b>Bagging</b>	58.85	58.50	52.46	91.27	0.52	0.88
<b>Bayesian</b>	49.25	64.35	48.18	89.11	0.47	0.85
<b>j48</b>	48.51	62.47	47.18	89.22	0.46	0.78
<b>Random Trees</b>	48.31	51.62	45.35	90.14	0.43	0.74
<b>With Balancing</b>						
<b>ML</b>	<b>Pr</b>	<b>Rc</b>	<b><math>F_1</math></b>	<b>Acc</b>	<b>MCC</b>	<b>AUC</b>
<b>Random Forests</b>	47.49	78.75	56.45	89.52	0.52	0.89
<b>Bagging</b>	28.42	83.17	38.91	75.25	0.31	0.86
<b>Bayesian</b>	15.68	98.04	23.84	21.70	0.06	0.83
<b>j48</b>	35.73	83.41	46.89	83.85	0.43	0.82
<b>Random Trees</b>	31.49	63.21	36.87	80.76	0.30	0.76

Table 4.5 reports the cross-project prediction results for each system, using the best classifier, Random Forests, and using balancing or not. The top part of the table is without balancing results and bottom part is with rebalancing using SMOTE. For the balanced dataset, Random Forests machine learner performs the best on the same systems as in within-project prediction. The systems with the lowest percentage of SATD methods are also the ones with the weakest performance results, namely JRUBY, JEDIT and ANT. JRUBY’s performances are significantly worse than in within-project prediction but it is the only system that experiences this decrease, the 8 others are almost all improving. These systems have a low percentage of SATD methods ( $< 2.15\%$ ) and can’t achieve a  $F_1$  score  $> 37\%$ , the other 6 systems all have a  $F_1$  score  $> 53\%$ . We notice that, even though SQUIRREL also have a small amount of SATD methods (1.42%), however, it still achieves a precision of 48.75% and a recall of 70.62%. It shows that not only the number of SATDs but also the features and context of these SATDs is important for the prediction quality of a classifier. Further analysis of the characteristics of methods labeled as SATD in JRUBY, JEDIT and ANT would be necessary to try and understand their low performances. These SATDs from the testing set could greatly differ from the ones in the training set. JFREECHART still have the best performance values (precision of 94.89%, recall of 95.98% and  $F_1$  score 95.43%) with ARGOUML being pretty close (precision of 94.46%, recall of 88.29% and  $F_1$  score 91.27%).

Table 4.5 Cross-project prediction: results of Random Forests for each system, without and with SMOTE balancing.

<b>Without Balancing</b>						
<b>System</b>	<b>Pr</b>	<b>Rc</b>	<b>F<sub>1</sub></b>	<b>Acc</b>	<b>MCC</b>	<b>AUC</b>
Ant	27.94	53.52	36.71	98.23	0.38	0.97
ArgoUML	94.46	88.29	91.27	92.72	0.85	0.98
Columba	67.84	43.88	53.29	92.19	0.51	0.92
Hibernate	72.84	52.10	60.75	96.74	0.60	0.95
jEdit	35.90	24.78	29.32	96.55	0.28	0.91
jFreeChart	94.89	95.98	95.43	98.05	0.94	0.99
jMeter	70.51	59.76	64.69	95.55	0.63	0.91
jRuby	91.89	5.11	9.69	58.32	0.15	0.75
Squirrel	48.75	70.62	57.86	98.63	0.58	0.97
<b>With Balancing</b>						
<b>System</b>	<b>Pr</b>	<b>Rc</b>	<b>F<sub>1</sub></b>	<b>Acc</b>	<b>MCC</b>	<b>AUC</b>
Ant	13.56	71.83	22.82	95.34	0.30	0.96
ArgoUML	89.74	92.65	91.18	92.27	0.84	0.96
Columba	49.01	69.06	57.33	89.56	0.53	0.94
Hibernate	52.61	68.87	59.66	95.49	0.58	0.95
jEdit	20.70	57.52	30.44	92.42	0.31	0.72
jFreeChart	84.85	96.81	90.44	95.67	0.88	0.98
jMeter	46.05	79.05	58.19	92.25	0.57	0.91
jRuby	50.50	93.10	65.48	57.09	0.28	0.64
Squirrel	20.42	79.90	32.53	95.61	0.39	0.93

They both have MCC values  $> 0.85$ , which translates to very strong correlation.

For the balanced dataset, results do not seem to be improving. Some systems benefit from the rebalancing on certain levels and others do not. In other words, the results are in line with what is obtained without balancing, or even lower. As expected, recall increases at the expense of precision. Accuracy is generally lower and no real benefits are observed on MCC and AUC values. ARGOUML achieves the highest  $F_1$  score (91.18%) with JFREECHART being really close to it (90.44%). The only system that really benefits from rebalancing is JRUBY with the following improvements: recall +87.99% and  $F_1$  score +55.79%. Precision obviously decreased but is still at a reasonable value of 50.50%.

To summarize, we can conclude that SMOTE rebalancing does not help a lot because (i)

the very limited samples of positive examples is not enough to act as a seed for the generation of artificial instances (ii) static analysis warnings are sparse and have a boolean nature, which is not appropriate for a proper usage of SMOTE. We can also conclude that cross-project prediction can be very beneficial, except for the systems with a small amount of SATDs. The main reason is that, for cross-project prediction, the number of SATD methods in the training set is larger than for within-project prediction.

Table 4.6 Top 10 discriminant features (cross-project prediction). (M): source code metrics, (CS): CheckStyle checks, (P): PMD checks.

Metric	Ant	ArgoUML	Columba	Hibernate	jEdit	jFreeChart	jMeter	jRuby	Squirrel
Readability (M)	1	1	1	1	1	1	1	1	1
LOC (M)	2	2	3	2	2	2	2	2	2
CommentNbr (M)	7	3	4	3	3	4	4	3	3
DeclNbr (M)	4	4	2	4	4	3	3	4	4
ExprStmtNbr (M)	5	5	5	5	5	5	5	5	5
McCabe (M)	6	6	6	6	6	6	6	6	6
ParNbr (M)	3	7	7	7	7	7	7	7	7
LocalVariableCouldBeFinal (P)	10	9	9	8	10	8	10	10	8
MethodArgumentCouldBeFinal (P)	—	10	10	10	8	9	8	8	7
FinalParameters (CS)	8	—	8	9	9	—	8	8	8
LineLength (CS)	9	8	—	—	—	10	—	—	10



Table 4.6 reports the top 10 features in cross-project prediction according to the MDI technique. The same features as in the within-project prediction are at the top, the most important being the source code metrics. *Readability* is still the feature playing the biggest role, for all the systems, followed by *LOC* once again and *CommentNbr* which moves up 4 spots. *ParNbr* drops a couple of spots and becomes less important than other metrics capturing the code size and complexity, namely *DeclNbr*, *ExprStmtNbr* and *McCabe*. In within-project prediction, 22 warning checks were in the top 10 of at least one system, in cross-project prediction, there are only 4 of them (*LocalVariableCouldBeFinal*, *MethodArgumentCouldBeFinal*, *FinalParameters* and *LineLength*). However, these checks are in the top 10 of more systems ( $> 4$ ). These checks are related to declaring final variables, parameters not being reassigned and the length of lines. Again, two checks seem correlated, namely *FinalParameters* and *MethodArgumentCouldBeFinal*. Both were kept after the Spearman’s analysis because the latter recommends the argument to be FINAL only if it is not reassigned, *textitFinalParameters* does not.

**RQ<sub>2</sub> summary:** Results from the cross-project prediction are similar to the within-project prediction: Random Forests is the machine learner which performs the best, rebalancing does not provide significant performance improvements, the same systems achieve the best results. However, cross-project prediction globally achieves better performance values in recommending technical debts to self admit because of a larger and more diverse dataset. Code readability, size and complexity are the main characteristics used to recommend design SATD.

#### 4.1.3 How would a method-level smell detector compare with TEDIOUS?

Table 4.7 Overall DECOR Performances in predicting SATD (the last line reports results for default thresholds).

Percentile	Long Method (LM)					Long Parameter List (LPL)					LM $\cup$ LPL				
	Prec.	Rec.	F <sub>1</sub>	Acc.	MCC	Prec.	Rec.	F <sub>1</sub>	Acc.	MCC	Prec.	Rec.	F <sub>1</sub>	Acc.	MCC
0.50	7.76	55.18	13.60	54.01	0.05	11.93	43.91	18.76	75.06	0.12	7.93	68.28	14.21	45.91	0.06
0.55	8.31	53.53	14.38	58.19	0.06	11.93	43.91	18.76	75.06	0.12	8.35	67.80	14.87	49.09	0.08
0.60	8.47	49.26	14.46	61.77	0.06	11.93	43.91	18.76	75.06	0.12	8.75	67.14	15.48	51.89	0.09
0.65	8.88	46.86	14.93	64.98	0.07	11.93	43.91	18.76	75.06	0.12	9.07	65.97	15.94	54.36	0.10
0.70	9.83	43.70	16.05	70.01	0.08	11.93	43.91	18.76	75.06	0.12	9.56	63.71	16.62	58.07	0.11
0.75	11.36	40.41	17.74	75.41	0.11	11.93	43.91	18.76	75.06	0.12	10.27	61.88	17.61	62.02	0.12
0.80	12.59	36.66	18.74	79.15	0.12	17.62	33.30	23.05	85.41	0.17	12.74	53.53	20.58	72.89	0.15
0.85	14.55	31.72	19.95	83.30	0.13	17.62	33.30	23.05	85.41	0.17	14.14	50.77	22.11	76.54	0.17
0.90	15.74	23.62	18.89	86.69	0.12	13.52	12.58	13.03	88.99	0.07	14.16	31.76	19.58	82.89	0.13
0.95	24.50	18.48	21.07	90.92	0.17	14.91	7.09	9.61	91.25	0.06	19.58	22.59	20.98	88.83	0.15
Default	11.36	40.41	17.73	75.41	0.11	17.62	33.29	23.04	85.41	0.17	11.58	54.69	19.12	69.64	0.13

Table 4.7 reports the overall DECOR performances in predicting SATD. They rely in the detection of *Long Method* and *Long Parameter List* smells by DECOR, and the union of both. In other terms, we want to know how well this smell detector can recommend technical debts based on the detection of these smells. DECOR was tested with thresholds at different percentiles of LOC and number of parameters. The unions of the two smells are done for same threshold values.

As we see in the table, smell detection’s performances are never as good as TEDIUS’s performances. Precision is always  $< 25\%$ , recall is always  $< 70\%$ ,  $F_1$  score is at most  $23.05\%$  and MCC values are all  $< 0.17$ , which translates to low correlation. *Long Parameter List* gives a better balance than *Long Method* between precision and recall, and slightly better results. The union of both gives decent recall values but generally low precision and it does not seem beneficial to the predictions’ performances.

**RQ<sub>3</sub> summary:** LOC and number of parameters metrics play an important role in within-project and cross-project predictions using TEDIUS. However, Long Method and Long Parameter List smell detectors of DECOR are not able to achieve performances comparable to TEDIUS.

#### 4.1.4 Qualitative discussion of false positive and false negatives

In this section, we discuss some examples out of 100 reported SATD methods that we manually inspected. The purpose behind this analysis is to explain cases where TEDIUS correctly or incorrectly classified SATD.

As examples of **true positives**, we have in ARGUML two methods labeled as SATD with different source code metrics values: *createFlow* in class COREFACTORYEUMLIPL and *invokeFeature* in class MODELACCESSMODELINTERPRETER. The first method has a *Readability*  $\approx 1$ , *LOC* = 2 and *McCabe* = 1. The second method has a *Readability* = 0, *LOC* = 755 and *McCabe* = 178. Even though both methods have obvious differences in the values of features defining them, TEDIUS was still able to detect them as being SATD prone. It proves that our approach can detect a wide variety of methods, based on their characteristics, containing a technical debt.

As an example of **false positive**, we have in JEDIT the method *initialize* in class RE with the following characteristics: *LOC* = 511, *NbParameters* = 5, *NbCalls* = 197, *NbDeclarations* = 32, *NbExpressions* = 618, *NbComments* = 97, *McCabe* = 102 and *Readability* = 0. The readability is obviously null considering the size of the method. TEDIUS clearly classified this method has a SATD while it is not, it plays a major role in the

class and is intrinsically complex. It may not contain a technical debt, but it may require some improvements to make it more understandable. Recommendations on such long and complex methods should not be worthless or annoying for developers. It should be taken as a hint that this kind of method has to be carefully implemented because of their complex nature, making sure that it is as readable and understandable as it can be.

As an example of **false negative**, we have in COLUMBA the method *start* in class COLUMBASERVER that is labeled as a design SATD but was classified as a non-SATD method by TEDIOUS. The SATD comment linked to the method is positioned immediately after an "if" statement and it says *"something is very wrong here"*. The developer intentionally mentions that the block of code is problematic, consequently leading external viewers to believe that a technical debt may be present. However, if such viewer analyzes the structure of the method, nothing could be considered as a symptom of a technical debt presence. This means that there is a deeper level to the characteristics defining a technical debt, other than structural and source code metrics. The TD in this case could be justified if we look at the bigger picture of the class or its context, not only its metrics. In other words, there are cases where TEDIOUS could not properly identify the presence of technical debts only using source code and structural metrics, which limits its applicability.

## 4.2 Threats to Validity

Here are the threats to validity of our study, based on the guidelines for case study research (Yin, 2013). We identified 5 threats: construct, internal, conclusion, reliability and external validity threat.

### 4.2.1 Construct validity

*Construct validity* threats concern the relationship between theory and observation. These threats are mainly due to measurement errors of metrics and labeled design SATD. Different calculation processes can result in different values of source code metrics, and the same goes for warnings obtained from static analysis tools. We used CheckStyle and PMD, but several other tools are available.

As for the SATD, we used the dataset from Maldonado et al. (2017b), where they annotated comments, labeling them as SATD or not. We used this information to build our oracle. Some preprocessing had to be done because the information was gathered at file-level, and not method-level. Pattern matching was performed to link SATD comments to their respective methods, which may have introduced some imprecisions. We established a strict

threshold to match SATD comments, which could be revised. Indeed, we only accepted the exact identity of comments from the dataset of Maldonado et al. (2017b) with the ones from the source code. Not all comments were matched using this approach because of a different processing chain, consequently, some methods which are in fact containing a technical debt were not be tagged as such. In the future, we plan to revise those matches which are close to being perfect but are not, to draw a more accurate picture of the systems.

This aspect can be detrimental and beneficial for TEDIOUS. On one side, the learning phase is more difficult since the process creates more false negatives (methods tagged as non-SATD but that are SATD). On the other side, these false negatives would make a more balanced dataset, if they can be traced back by our approach, leading to improved performance. Additionally, any errors made by Maldonado et al. (2017b) when analyzing the systems would have an impact on the accuracy of our approach. Finally, some comments in the dataset exactly matched more than one comment in the source code. When we encountered such cases, we tagged these comments as *Maybe*, since we could not exactly classify them.

#### 4.2.2 Internal validity

*Internal Validity* threats concern internal factors that could have influenced our results. Several of them can be identified, (i) machine learners have been applied with default settings, (ii) CheckStyle and PMD were used with default configurations, (iii) source code metrics were computed with *srcML* and (iv) EMF project was not used in our dataset.

The fact that machine learners were built with default configurations only means that better results could have been obtained with a proper parameter optimization. In the worst case, this only means that our results are the lower-bound of what could be obtained. For Checkstyle, the default rules provided by the tool were used, the same goes for PMD. Similarly to the machine learners, a proper calibration of rules could have resulted in a different set of warnings which would have depicted a more accurate view of the systems. Consequently, the usefulness of checks could have been improved for the prediction. In fact, we plan to use SATD to help customize CheckStyle and PMD rules.

Source code metrics were computed using *srcML* (Collard et al., 2013) (except for the readability metric which was computed using the tool of Buse and Weimer (2008)), therefore, other metric extractors could provide different results. However, the purpose of this study was not to evaluate our approach for specific static analysis tools and metri extractors. These tools were selected because of their ease of use and their popularity. They were complementary to the realisation of TEDIOUS. The main purpose of our work was to highlight the potential

of learning technical debt to self-admit from source code features.

We did not include EMF project to our dataset because we were unable to download the archive release 2.4.1. Since we already have 9 systems, some with similar amounts of classes (ARGOUML, HIBERNATE and COLUMBA) or a smaller amount (SQUIRREL), we believe skipping EMF will not bias our results, even though it is the largest in terms of LOC.

#### 4.2.3 Conclusion validity

*Conclusion Validity* threats concern the relationship between treatments and outcomes. To avoid these threats, we use appropriate metrics to quantify the performance of machine learners (AUC and MCC) and tools to compute the importance of learning features (MDI). We use these diagnostics in addition to thresholds to define the acceptability of our outcomes ( $AUC > 0.5$  and  $MCC > 0$ , the closer to 1.0 the better).

#### 4.2.4 Reliability validity

*Reliability validity* threats concern the replicability of our study. We attempt to provide, as far as we can, all the necessary information to replicate our study. We plan to share a replication package containing: source code, raw data and scripts.

#### 4.2.5 External validity

*External validity* threats concern the generalization of our results. We cannot guarantee that our results can be generalized to all Java programs even though we used the same systems from a previous study (Maldonado et al., 2017b) and even if the systems cover different domains. Our dataset is somewhat limited since we only have 9 systems. As future work, more studies are required to verify the extent at which TEDIOUS can be employed and how our findings can be generalized to other projects, domains and programming languages.

## CHAPTER 5 CONVOLUTIONAL NEURAL NETWORK WITH COMMENTS AND SOURCE CODE

### 5.1 Convolutional Neural Network

Several machine learners were tested with TEDIOUS, using source code metrics as training features. Results were promising but the approach asked for a lot of preparation work: building the XML representation of the Java code, pattern matching between comments from the dataset and the source code, extracting the source code metrics, extracting the warning raised by static analysis tools and feature preprocessing. These additional steps take time and knowledge of the whole process. Consequently, we wanted to try a novel approach, easier and faster to set up. We decided to test a Convolutional Neural Network (CNN) with Natural Language Processing (NLP) directly on the Java source code of software projects.

The idea of using a CNN was inspired by a paper written by Kim (2014). He used a CNN for sentence-level classification tasks and showed that you can achieve excellent performance results with little parameter calibration. He tested his model on several benchmarks. Similar work has been pursued concerning sentiment analysis of short texts (Dos Santos and Gatti, 2014). More specifically, they analyzed Twitter messages and movie reviews, and tried to classify them as being of positive or negative sentiment. Our idea is similar to these studies, we plan to use a CNN to classify comments and/or methods using the source code directly instead of features, linking them to technical debt or not.

Typically, convolutional neural networks were employed for image classification (Krizhevsky et al., 2012), however, as mentioned previously, this type of neural network has been used recently combined with NLP. To describe CNN in further details, we can think of a convolution as a window sliding across a whole matrix, acting as a filter. For images, this matrix contains pixels, for words and sentences, it contains word vectors (word embeddings). In image classification, filters slide over local batches, in NLP, they slide over entire rows since a row is typically a single word embedded into a row matrix of the size of the embedding dimension. To implement a CNN, you just have to add several layers of these convolutions, where each of these layers have a specific task and act as different filters. CNNs are very fast and efficient in terms of representation, which means they give good representations without needing the whole vocabulary of a dataset.

The main purpose of this study was to explain, test and analysis TEDIOUS, our machine

learning approach using source code features. The next sections will describe the other approach using a CNN, but at a more general level than for TEDIOUS since we are still at a preliminary stage. Since some steps from Chapter 3 are replicated in our CNN approach, they will be explained rapidly in order to avoid redundancy. However, we still judged interesting to present the initial results of this new promising method.

## 5.2 The Approach

This section will describe the steps followed to design this new approach, a convolutional neural network combined with natural language processing to identify technical debts to self-admit. Additional information will be shared on the characteristics of this machine learner and how it works. Like TEDIOUS, this approach works at method-level since it is granularity at which we are most likely to detect TD (Potdar and Shihab, 2014). In other terms, this approach is able to detect if a technical debt is contained in a method or not.

As shown in Figure 5.1, two datasets are required to build our model: the training and test set. The training set contains labeled data, which is source code where SATD are known. The test set contains unlabeled data, which can be any source code where we want to recommend where technical debts should be admitted. The presence and location of TDs are unknown in the test set.

For the training set, various combinations of source code and comments, labeled as containing a SATD or not, are extracted: source code comments only, source code with comments, source code without comments and source code partially with comments. It is essential to have this classification because the CNN is based on supervised learning. Pattern matching using comments from the dataset of Maldonado et al. (2017b) is employed to classify the methods and comments.

Once all the source code is extracted and classified, some preprocessing has to be done. The source code is tokenized, the purpose being to demarcate and transform the source code into a string of word tokens. The comments specifically are cleaned up to remove extra spaces, non-ASCII characters, upper case letters, etc. Once the source code is preprocessed, word embeddings is performed, which means strings of tokens are transformed into vectors of numerical values using word2vec tool (wor). With the source code preprocessed and the oracle built, the model can be trained with the CNN.

In parallel, the test set is prepared. The same combinations of source code and comments are extracted, but SATD matching is not required because the data is unlabeled and we want to predict the presence of technical debts. The matching of SATDs is only required for the





generated using the srcML tool (Collard et al., 2013). SATD comments from the dataset of Maldonado et al. (2017a) were linked to their respective methods in order to classify them as containing a technical debt or not, to build the oracle. The same rules were followed, as explained in section 3.1.1. Once the XML representation is obtained, the different dataset combinations can be generated.

The first combination is the *source code comments only*. They are extracted from the dataset of comments provided by Maldonado et al. (2017b). Comments can be encountered under different natures: single line, multiple lines or block. It is important to specify that not only design debts were retained but all of them, namely: defect, design, documentation, implementation and test. We decided to use as many SATD-methods as possible in order to have the best chances at getting good predictions results. By using different types of technical debts, we decrease the unbalance of the dataset by adding more positive examples.

The second combination is the *source code with comments* where the complete XML representation of the source code is used. The third combination is the *source code without comments* where the XML representation is parsed to remove comments. The fourth combination is the *source code partially with comments*, which means only comments related to SATD are removed. The reason behind this removal is to be sure to avoid the CNN model being a self-prophecy. For these three datasets, only design and implementation TDs are retained, to be more in line with the dataset used by TEDIOUS. The details of the process behind the extraction of each combination will be explained in the Source Code Preprocessing section.

### 5.2.2 Identification of Self-Admitted Technical Debt

Like TEDIOUS, the purpose of this approach is not to propose a new way to detect SATD using information from comments. However, will still needed a classified dataset in order to train our CNN model. We used the dataset of Maldonado et al. (2017b), which contains a classification of 10 open source projects, where methods are tagged as containing a technical debt or not. Various types of TDs are considered, depending on the source code combination. The dataset reports SATD at file-level instead of method-level, consequently, some preprocessing had to be performed. With pattern matching, SATD comments were tagged to their related methods.

### 5.2.3 Source Code Preprocessing and Word Embeddings

The source code is extracted in a XML format, which is not quite compatible for the machine learner to train on. The files have to be tokenized. Instead of using standard coding lexicon (conditional statements, variables types and names, parameters declaration) and separators (brackets, parentheses, spaces) directly in our dataset, demarcations are added (*i.e.* *begin\_type*, *end\_type*) to transform the structure into series of word tokens. For comments, strings are normalized: extra spaces are removed, upper cases are transformed to lower cases, non-ASCII are removed as well as new lines. Also, if a comment is matched with a SATD pattern, it will be printed as:

```
COMMENT__BEGIN__SATD COMMENT-NORMALIZED-TEXT COMMENT__END__SATD
```

This step is essential to build the oracle and the dataset partially with comments. By explicitly defining comments tagged as SATD in this format, it is easy to parse the tokenized dataset in order to remove them. Comments are linked to their respective method, so a method linked to a SATD comment will also be tagged as SATD. By tokenizing the source code, it is also easier to remove the comments globally, if necessary. Transforming the source code into tokens also acts as a normalization process, which will make the word embedding process more efficient.

Word embeddings is the process of transforming words and phrases from the dataset into vectors of real number. Word2vec models were used to generate word embeddings. The vector dimension we used is 100, we tried to have a balance between a proper representation of words and processing time. A new word embedding was generated for each source code combination since they are all different in some ways.

Finally, the methods extracted are all tagged as positive or negative examples. In order for the CNN to be trained and tested, these methods have to be divided in 4 basic files: POSITIVE-TRAIN, NEGATIVE-TRAIN, POSITIVE-TEST and NEGATIVE-TEST. Each fold of the cross validation contains these 4 files, consequently, for a 10-fold cross validation, 40 files are required. Instead of using an additional feature to classify each method in a single file, the files act as classifiers. Here is a detailed definition of each file, considering a 10-fold cross validation:

- *Positive-Train*: Training set containing SATD methods (90% of all positive examples)
- *Negative-Train*: Training set containing non-SATD methods (90% of all negative examples)
- *Positive-Test*: Testing set containing SATD methods (10% of all positive examples)

- *Negative-Test*: Testing set containing non-SATD methods (10% of all negative examples)

#### 5.2.4 Building and Applying CNN

So far, we extracted source code from various projects, with or without comments, we identified SATD methods, we preprocessed the dataset and performed a word embedding. The only step remaining is building and applying the convolutional neural network. Four sets are required, as described in the previous section: two sets for training, one containing SATD methods and the other not, and two sets for testing, one of positive and the other of negative examples. The sets contain the tokenized source code of the nine studied projects.

Figure 5.2 provides an overview of the CNN process. To increase the training speed and to benefit as much as possible from the processing power available, several threads are created. One thread is started for each fold, using a pair of previously generated training files. Up to five threads can be processed at the same time. The next actions are all performed simultaneously on each thread, until we have models trained for all folds.

The evaluation process consists of two main phases: the training and the testing phase. In the former, some data preparation is required: load the two training sets, build the vocabulary, shuffle, and split the dataset in a training and development set. The development set is used to tune parameters of the CNN and to prevent it from over-fitting. Afterwards, the CNN is built using user-defined parameters and default values. In our case, mainly the default configuration is considered. The training procedure is defined and summaries are generated for: loss, accuracy, train, development and model. Then, variables are initialized, such as embedding vectors, and training batches generated. Finally, a training loop is executed where a training and evaluation step are repeated. The trained model is saved multiple times during the loop and the last one is used for the testing.

The testing phase can start once the training is finished. Data preparation is also required for this step: load the two testing sets and map them into the vocabulary. Afterwards, the meta graph and the variables from the model previously saved are loaded. Testing batches are generated and tensors we want to evaluate are determined. We can then start the testing loop where predictions are made. Once over, performance metrics can be computed, namely: accuracy, recall, precision, specificity and  $F_1$ . These metrics are saved in a different file from the predictions made on each method. The final step consists of combining the performance metrics of all models for further analysis.

### 5.3 Study Definition

The goal of this new approach is to assess the prediction performance of a convolutional neural network in recommending technical debts to self-admit. The focus is the same as for TEDIOUS, enhancing the source code quality by keeping track of TDs. The perspective is to be able to suggest to developers, more accurately than with TEDIOUS, when to admit technical debts. We aim to address four research questions:

- **RQ1:** How does a CNN work for recommending SATD with source code comments only?
- **RQ2:** How does a CNN work for recommending SATD with source code with comments?
- **RQ3:** How does a CNN work for recommending SATD with source code without comments?
- **RQ4:** How does a CNN work for recommending SATD with source code partially with comments?

#### 5.3.1 Dataset

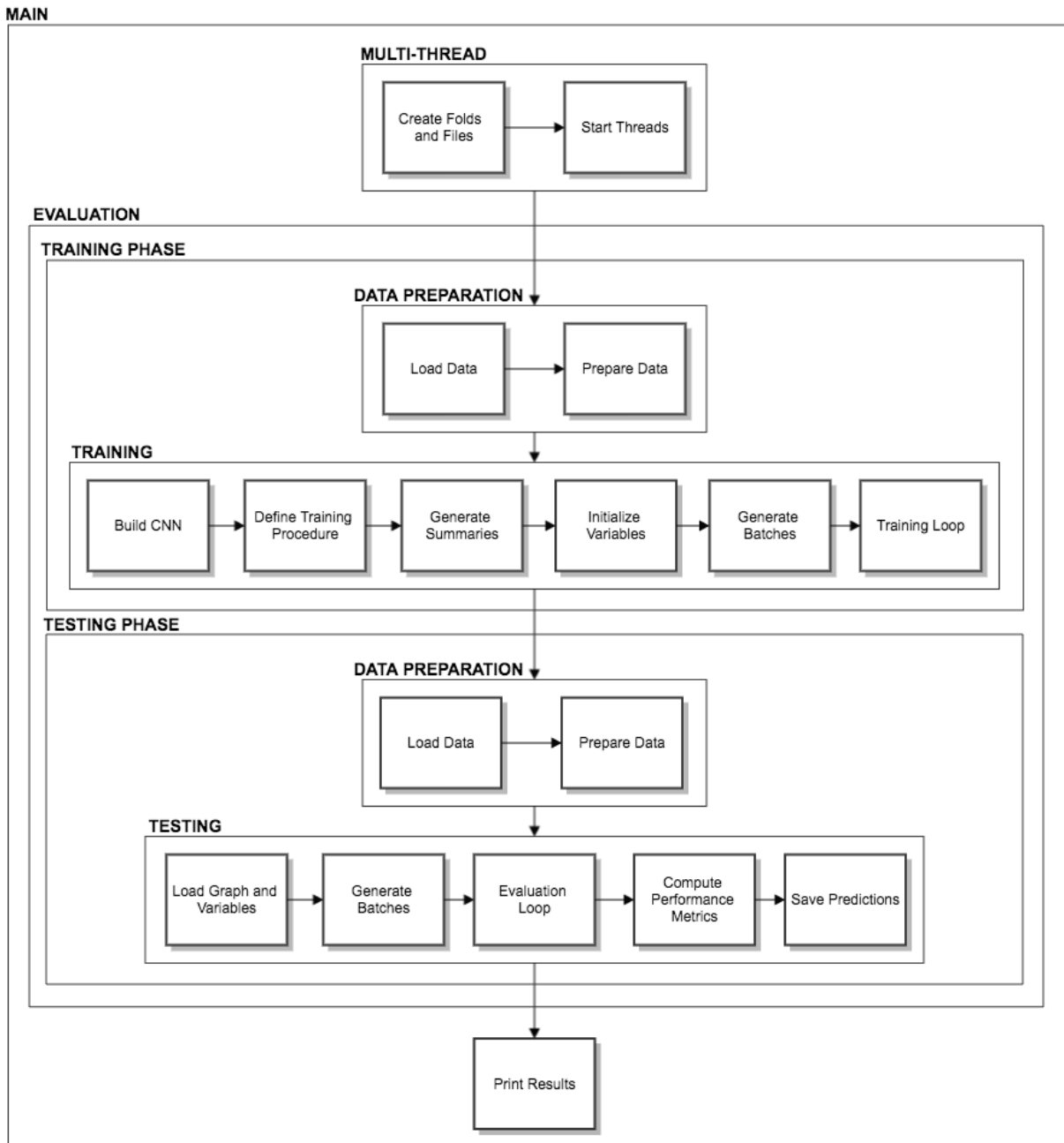


Figure 5.2 Process for building and applying a CNN.

Table 5.1 Characteristics of the studied projects.

Project	Release	Number of				Number of Comments ∈ Methods	Number of Design SATD		% of Methods with design SATD
		Files	Classes	Methods	Comments		∉ Methods	∈ Methods	
Ant	1.7.0	1,113	1,575	11,052	20,325	13,359	1	57	0.5%
ArgoUML	0.34	1,922	2,579	14,346	64,393	17,722	203	425	2%
Columba	1.4	1,549	1,884	7,035	33,415	10,305	8	418	5%
Hibernate	3.3.2 GA	2,129	2,529	17,405	15,901	9,073	21	377	2%
jEdit	4.2	394	889	4,785	15,468	10,894	6	77	2%
jFreeChart	1.0.19	1,017	1,091	10,343	22,827	15,412	4	1,881	18%
jMeter	2.1	1,048	1,328	8,680	19,721	12,672	95	424	5%
jRuby	1.4.0	970	2,063	14,163	10,599	7,809	16	275	2%
Squirrel	3.0.3	2,325	4,123	16,648	25,216	15,574	35	173	1%

To evaluate this new approach, the same dataset was used as in TEDIOUS (Maldonado et al., 2017b). The methods are already classified as SATD or not, and Table 5.1 summarizes the characteristics of all studied projects. Various information describe the content and nature of each project. This table was already presented in Section 3.2.1. However, a brief overview is still necessary to reiterate important facts.

There are some disparities between the results we obtained when analyzing the studies and what Maldonado et al. (2017b) obtained. However, this does not really represent an issue since many of these differences concern classes while our CNN approach is method-level based, like TEDIOUS. This aspect is also important since we clearly see a prevalence of method-related rather than class-related SATD. Out of all methods in a project, only a very small amount contains a technical debt, making the dataset highly unbalanced. As we will discuss in the analysis of results, the lower the amount of technical debts in a system, the lower the prediction performance. Since the dataset from Maldonado et al. (2017b) classified classes instead of methods, we performed pattern matching between known SATD comments and comments attached to methods in the dataset.

### 5.3.2 Analysis Method

For **RQ1**, we want to know how a convolutional neural network with source code comments only work for recommending SATD within-project. We also want to compare the results with the within-project predictions of TEDIOUS. A 10-fold cross validation was performed on each project, like for TEDIOUS, and the performance values are averaged over the 10 iterations. The same process is followed for **RQ2**, **RQ3** and **RQ4**.

Standard performance metrics on the SATD category were computed to evaluate our automated classification approach: precision, recall,  $F_1$  score and accuracy. Precision is the percentage of relevant instances of methods predicted as SATD among all retrieved instances. Recall is the percentage of relevant instances of SATD methods that have been retrieved over all relevant instances.  $F_1$  score is the harmonic mean between precision and recall. Accuracy is the total number of methods correctly predicted, whether it is SATD-related or not, among all analyzed methods.

Unfortunately, metrics such as MCC, ROC and importance of features were not computed for this approach. However, we still have enough information to evaluate and compare each approach. The downside is that it will be more difficult to take into account the effect of chance on predictions. Overall, what we look for in a good classifier is a balance between precision and recall while aiming for the highest  $F_1$  score. We want to detect as many technical debts as possible while being correct in our predictions.



## 5.4 Study Results

This section reports the results obtained using various combinations of source code. Performance metrics are presented in tables and further analysis is provided textually, discussing the metrics and comparing them with TEDIIOUS.

### 5.4.1 Source Code Comments Only

Table 5.2 reports the within-project performance results of a 10-fold cross validation on each system using our convolutional neural network and source code comments only. We computed the average for the 10 folds of each system and for the complete dataset. Since we already had the comments preprocessed for TEDIIOUS, this dataset was a good start to test our CNN approach.

Two systems perform significantly worse than the others, namely ANT and JEDIT. We face the same problem as in TEDIIOUS, where the very low percentage of SATD methods (ANT has 0.5% and JEDIT has 2%) in some systems directly affects the performance of the CNN. ANT has a precision of 93.33%, recall of 10.77% and  $F_1$  score of 19.31%. JEDIT is a little better, it has a precision of 82.95%, recall of 29.32% and  $F_1$  score of 43.32%. However, if we compare with results from TEDIIOUS, we notice a significant improvement in precision while maintaining a similar recall for these two systems.

As for the other systems, the precision is  $> 91\%$ , the recall is  $> 65\%$  and the  $F_1 > 77\%$ . Differently from TEDIIOUS where the best results were obtained with JFREECHART, ARGOUML is the system where the CNN performed the best (precision 91.21%, recall 90.94% and  $F_1$  91.07%). JFREECHART still obtained the best precision (100%) but other projects such as JRUBY or JMETER provided more balanced performance values. We have to be careful when comparing results in this scenario because all types of technical debts were considered whereas TEDIIOUS only analyzed design debts.

However, on first look, it seems that the CNN approach using source code is an improvement of TEDIIOUS using source code features. The total average precision, recall and  $F_1$  score is even higher than the best system using TEDIIOUS. Further testing is needed to provide a better understanding of the performance of the CNN, which will be accomplished in the next sections.

Table 5.2 Within-project prediction: results of CNN for each system using source code comments only

<b>Source Code Comments Only</b>				
<b>System</b>	<b>Pr</b>	<b>Rc</b>	<b><math>F_1</math></b>	<b>Acc</b>
Ant	93.33	10.77	19.31	97.02
ArgoUML	91.21	90.94	91.07	97.24
Columba	97.12	71.05	82.07	99.08
Hibernate	95.29	73.19	82.79	95.12
jEdit	82.95	29.32	43.32	98.09
jFreeChart	100.00	69.38	81.92	98.50
jMeter	95.25	75.95	84.51	98.71
jQuery	96.14	87.17	91.43	97.89
Squirrel	95.81	65.59	77.87	98.51
<b>Total</b>	<b>93.63</b>	<b>76.17</b>	<b>84.00</b>	<b>97.99</b>

#### 5.4.2 Source Code With Comments

Using source code comments only is an interesting first step to train a convolutional neural network to predict technical debts, especially if we aim at addressing the issue of self-admitted technical debts. However, it would also be interesting to see how well a CNN can perform using the entirety of a project’s source code, code and comments included. We experimented with such a dataset and obtained the results reported in Table 5.3 for a within project 10-fold cross validation.

Again, the worst results were obtained for ANT and JEDIT. However, compared to source code comments only, ANT improved its precision by +1.91%, recall by +55.90% and  $F_1$  by +59.12, and JEDIT improved its precision to 100% but suffered some losses in its recall and  $F_1$  score. We notice that the unbalance of the dataset is still an issue for the CNN but these results are still better than what we obtained with TEDIOUS.

As for the other systems, the precision varies between [93.62% – 98.57%], the recall between [76.80% – 90.72%] and the  $F_1$  score between [84.67% – 94.09%]. Precision is generally slightly better and the recall gains a decent improvement compared to the source code comments only dataset. The best results were obtained with JFREECHART (precision 97.73%,

Table 5.3 Within-project prediction: results of CNN for each system using source code with comments

<b>Source Code With Comments</b>				
<b>System</b>	<b>Pr</b>	<b>Rc</b>	<b><math>F_1</math></b>	<b>Acc</b>
Ant	95.24	66.67	78.43	99.81
ArgoUML	97.32	87.88	92.36	98.84
Columba	93.62	80.00	86.27	99.66
Hibernate	95.61	89.71	92.56	99.72
jEdit	100.00	21.00	34.71	98.25
jFreeChart	97.73	90.72	94.09	99.72
jMeter	96.45	82.61	88.99	99.45
jRuby	94.35	76.80	84.67	98.70
Squirrel	98.57	85.19	91.39	99.92
<b>Total</b>	<b>96.38</b>	<b>82.40</b>	<b>88.84</b>	<b>99.44</b>

recall 90.72% and  $F_1$  score 94.09%), like in TEDIOUS but not the previous dataset. This can be explained by the fact that we only used design and implementation debts, compared to all types of debt for source code comments only. Consequently, results with this dataset should normally be more similar to the results of TEDIOUS.

If we look at the average total performance values, there is an improvement compared to the source code comments only dataset: precision +2.75%, recall +6.23% and  $F_1$  +4.84%. Consequently, using the whole source code is also an improvement compared to TEDIOUS, in a pretty significant manner. We just tested the best case scenario where we have as much information as possible to train on, however, we also want to know how well a CNN can perform on a less than ideal software project.

#### 5.4.3 Source Code Without Comments

We trained our convolutional neural network on source code comments only and on source code in addition to comments. We obtained promising results, but we want know how well our machine learner can work with less training information. We generated another dataset, this time only containing the source code of the studied projects, eliminating the comments. We built such a dataset to replicate the worst case where a software project is lacking comments

Table 5.4 Within-project prediction: results of CNN for each system using source code without comments

<b>Source Code Without Comments</b>				
<b>System</b>	<b>Pr</b>	<b>Rc</b>	<b><math>F_1</math></b>	<b>Acc</b>
Ant	50.00	1.67	3.23	99.48
ArgoUML	89.78	37.27	52.68	94.67
Columba	84.21	14.55	24.81	98.81
Hibernate	79.66	27.65	41.05	98.43
jEdit	72.73	24.00	36.09	98.11
jFreeChart	73.68	17.72	28.57	97.85
jMeter	83.61	22.17	35.05	97.77
JRuby	95.27	56.40	70.85	97.84
Squirrel	88.89	17.78	29.63	99.56
<b>Total</b>	<b>88.18</b>	<b>33.68</b>	<b>48.75</b>	<b>98.12</b>

and to remove SATD comments related to their respective methods. Table 5.4 reports the performance results for each system using a 10-fold cross validation and source code without comments as the training set.

ANT is still the system where the CNN performs the worst (precision 50.00%, recall 1.67% and  $F_1$  3.23%), in line with every other experiment we performed so far. However, JEDIT is performing decently compared to previously and, surprisingly, JFREECHART is average even though it contains the most design debts. It seems the unbalance of the dataset does not correlate as much with the results since JRUBY obtains the best performance (precision 95.27%, recall 56.40% and  $F_1$  70.85%) only with 2% of methods with design SATD.

As for the other systems, performance metrics all decreased compared to the last two datasets, especially the recall. If we compare the total average, at the most, precision decreases of  $-8.21\%$ , recall of  $-48.72$  and  $F_1$  of  $-40.09\%$ . Compared to TEDIOUS, the precision is generally better but the recall rate worst. It would be difficult, with the available information, to determine which machine learner performs better between TEDIOUS and CNN with source code without comments. However, it is safe to say that they are at least similar performance wise, with TEDIOUS providing better recall and the CNN better precision.

Overall, it is obvious that removing comments from the dataset impacts the performance of the CNN at all levels. It is clear that they represent an important piece of information for the machine learner to train on and should be kept in the dataset. We also notice that not only the amount of technical debts in a system is important to obtain good performance, but the nature of technical debts and the content of the source code as well. When removing comments, we observed that different systems would perform better than previously and other worst, despite having the same amount of SATD-methods. Knowing the importance of comments, one more experiment would be interesting to complete to better understand why.

#### 5.4.4 Source Code Partially With Comments

So far, the best results were obtained with a dataset consisting of source code with comments. When removing all comments, we observed a significant loss in recall, and a modest one in precision. We now want to test an intermediate dataset where we keep all comments except the SATD comments manually analyzed by Maldonado et al. (2017b). The main reason behind the generation of this new dataset is to quantify the impact of these specific comments on the prediction performance and to know if they act as a self-prophecy. In other terms, we want to know how well our convolutional neural network can predict technical debts in methods if we remove comments self-admitting them. Table 5.5 reports the performance results for each system using a 10-fold cross validation and source code partially with comments.

#### **AJOUTER LA TABLE CROSS PROJECT DE GIULIO. LES COMMENTES LIES AUX METHODS SATD SONT ENLEVES POUR EVITER SELF PROPHECY**

All systems perform decently well and previously problematic ones, such as ANT and JEDIT, are not outsiders anymore. The precision varies between [87.23% – 100.00%], the recall between [39.09% – 68.78%] and the  $F_1$  score between [56.21% – 80.52%]. In other terms, the CNN is able to predict at least half of the technical debts in a system with a very high precision.

Compared to the dataset with all comments where results seemed somewhat dependent on the system, this one provides more balanced but weaker overall results. However, there is a net improvement compared to the dataset without comments. In fact, source code partially with comments positions itself right between the previous two datasets with a precision of 94.84%, recall of 58.83% and  $F_1$  score of 72.61%. Compared to TEDIOUS, our CNN with source code partially with comments is also an improvement.

We observe that SATD comments have an important impact on the prediction performance. The amount of comments removed is very small compared to the total, however,

Table 5.5 Within-project prediction: results of CNN for each system using source code partially with comments

<b>Source Code Partially With Comments</b>				
<b>System</b>	<b>Pr</b>	<b>Rc</b>	<b>F<sub>1</sub></b>	<b>Acc</b>
Ant	96.88	51.67	67.39	99.74
ArgoUML	95.40	60.81	74.28	96.65
Columba	100.00	39.09	56.21	99.18
Hibernate	87.68	54.41	67.15	98.95
jEdit	100.00	40.00	57.14	98.67
jFreeChart	93.68	68.78	79.32	99.13
jMeter	97.46	50.00	66.09	98.61
jQuery	97.44	68.60	80.52	98.45
Squirrel	87.23	45.56	59.85	99.68
<b>Total</b>	<b>94.84</b>	<b>58.83</b>	<b>72.61</b>	<b>98.82</b>

the impact on performance is not negligible, mostly on recall. It seems like comments, especially SATD-related, are important features for our machine learner to train on. We observe this fact in the way each system position themselves compared to others, some will benefit from keeping SATD-related comments and others will not. In addition, performance metrics globally decrease when removing comments.

## CHAPTER 6 CONCLUSION

### 6.1 Summary of Work

This study describes two approaches to recommend to developers when they should self-admit design technical debts. The main approach is TEDIOUS, a machine learner that uses features extracted from source code as independent variables and knowledge of SATD as dependent variables to recommend TD to be self-admitted. It is based on size, complexity, readability and checks from static analysis tools. The second approach, less developed than TEDIOUS, is a convolutional neural network using source code directly to recommend TD to be self-admitted. It is based on source code and comments.

Both approaches were evaluated on 9 projects manually analyzed and made publicly available by Maldonado et al. (2017b). For TEDIOUS, the within-project prediction gave on average a precision of 50%, recall of 52% and accuracy of 93% when recommending TDs. Oversampling was performed to compensate the highly unbalanced dataset (very few positive compared to negative instances) but without much benefits; it increased recall at the expense of precision. Cross-project prediction was also performed, with improved results compared to within-project. It gave on average a precision of 67%, recall of 55% and accuracy of 92% when recommending TDs. The best systems achieved a precision and recall rate  $> 88\%$ , namely JFREECHART and ARGOUML. Code readability, size and complexity played a major role in recommending design SATD, with static analysis tools being less important.

For the CNN approach, four experiments were conducted with no balancing performed. For *source code comments only* within-project prediction, an average precision of 93.63%, recall of 76.17% and accuracy 97.99% were obtained. For *source code with comments* within-project prediction, an average precision of 96.38%, recall of 82.40% and accuracy of 99.44% were obtained. Adding the implemented code to the dataset improved the results. For *source code without comments* within-project prediction, an average precision of 88.18%, recall of 33.68% and accuracy of 98.12% were obtained. Performance metrics were negatively affected by the removal of all comments. For *source code partially with comments* within-project prediction, an average precision of 94.84%, recall of 58.83% and accuracy of 98.82% were obtained, which is a better than no comments but worst than all comments included. **ADD CROSS PROJECT RESULTS.** Overall, each CNN experiment performed better than TEDIOUS.

## 6.2 Limitations of the Proposed Solution

TEDIOUS and our CNN approach have their share of limitations and constraints. The two approaches can't act as perfect classifiers because of the intrinsic nature of technical debts. You can try to describe methods with metrics and static analysis warnings, or use them as a whole, but there will always be a deeper level to their existence and a larger context that can be difficult for a machine learner to understand. We observed this aspect when qualitatively analyzing false negative examples of TEDIOUS. In other terms, the prediction performance of our proposed solution have a ceiling which is difficult to surpass.

For TEDIOUS, we are limited with the number of metrics and warnings we can use to train the machine learners. For the CNN, the number of LOC from the source code used for the dataset is also subject to a limit. The main reason behind this limitation is the processing time and computation power required (i) to extract these metrics and source code, and (ii) to train TEDIOUS and the CNN. We can't use as many training features as we want and have models trained in a decent amount of time with reasonable processing power.

In addition, there may be differences in feature values depending on the method to obtain them; the heavy preprocessing required to build datasets of TEDIOUS and the CNN approach can induce errors, and the manual classification of SATD comments is subject to human error. Also, default configurations only were used to collect warnings and train machine learners. Performance may be limited and could be increased by applying optimization on configuration parameters. Consequently, the results we obtained could be completely different, even though the same features are extracted, only because the process to extract them is different. In other terms, the replicability of our study is limited.

We can't assure that our results can be generalized to all Java projects even though we used systems previously studied (Maldonado et al., 2017b) which cover a wide variety of domains. Our dataset is limited, it only consists of 9 systems, and we cannot claim that TEDIOUS and the CNN can be accurate on every possible Java system. We already observe this fact in the various experiments we pursued. In addition, the applicability of our approaches is limited to Java programs only. Finally, the conclusion deduced from the analysis of the CNN results has to be taken with skepticism since it is still in its preliminary steps and the impact of randomness was not taken into account in its evaluation.

## 6.3 Future Work

Future work can be divided in two themes: applicability scenarios and improvement paths. Applicability scenarios are ideas on how TEDIOUS and the CNN approach could be used



concretely by developers in the industry. Improvement paths are tasks that have to be accomplished to improve and extend our work.

For future applications, our approaches could act as recommendation systems for developers, suggesting when to self-admit technical debts with comments, which was the main goal of our work. Also, they could complement static analysis tools by helping to customize warning checks raised by them. Our machine learners could learn rules from previously detected SATDs. Additionally, TEDIIOUS and our CNN could complement existing smell and anti pattern detectors, such as DECOR (Moha et al., 2010), to enhance their performance. Indeed, our study proved that TEDIIOUS could outperform a smell detector of Long Methods and Long Parameter List.

Many improvement and work paths are already planned for the future. Both TEDIIOUS and the CNN could benefit from configuration optimization. Only default parameters were used by the machine learners and extraction tools. More specifically, CNN results are still preliminary and performance metrics are still lacking. Further testing is required to better understand the real value of this approach. SATD comments were matched to methods with pattern matching, however, we retained only perfect matches, some comments did not match and others were very close to matching but were ultimately ignored. A revision of this process would be necessary to gather a more accurate picture of technical debts in systems.

As mentioned previously, our dataset is small and our approaches would benefit from a larger pool of examples to train on. More information could also be provided by adding other metrics or warnings to define methods. The same idea can be translated to the CNN by adding more source code. TEDIIOUS only detects design debts and it would be interesting to see how well it performs for the prediction of all types of technical debts. The CNN already predicts all types of debts and performs better than TEDIIOUS. We could also extend the application of our concept to other programming languages and domains.

Finally, TEDIIOUS is based on a Random Forests algorithm and we have a convolutional neural network which gives good prediction results. It would be interesting to test another popular machine learner used with Natural Language Processing, which is a Recurrent Neural Network (RNN).

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## APPENDIX A DÉMO

Texte de l'annexe A. Remarquez que la phrase précédente se termine par une lettre majuscule suivie d'un point. On indique explicitement cette situation à  $\text{\LaTeX}$  afin que ce dernier ajuste correctement l'espacement entre le point final de la phrase et le début de la phrase suivante.



## APPENDIX B    ENCORE UNE ANNEXE

Texte de l'annexe B en mode «landscape».

## APPENDIX C    UNE DERNIÈRE ANNEXE

Texte de l'annexe C.