A Machine-learning Based Ensemble Method For Anti-patterns Detection

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Abstract

Anti-patterns are poor solutions to recurring design problems. Several empirical studies have highlighted their negative impact on program comprehension, maintainability, as well as fault-proneness. A variety of detection approaches have been proposed to identify their occurrences in source code. However, these approaches can identify only a subset of the occurrences and report large numbers of false positives. Furthermore, a low agreement is generally observed among different approaches. Recent studies have shown the potential of machine-learning models to improve this situation. However, such algorithms require large sets of manually-produced training-data, which often limits their application in practice.

In this paper, we present SMAD (SMart Aggregation of Anti-patterns Detectors), a machine-learning based ensemble method to aggregate various anti-patterns detection approaches on the basis of their internal detection rules. We experiment SMAD on two well known anti-patterns, God Class and Feature Envy, and assess its performances on three open-source Java systems. Our results show that SMAD overcomes the previous limitations. First, our method clearly enhances the performances of the so aggregated approaches and outperforms competitive ensemble methods. Second, we show that such method can be used to generate reliable training data for machine-learning models from a reasonable number of manually-produced examples.

Keywords: Software Quality, Anti-patterns, Machine Learning, Ensemble Methods

1. Introduction

Fowler \cite{Fowler2002} defined design smells as symptoms of poor solutions to recurring design problems. These symptoms, also called anti-patterns, are typically introduced in object-oriented systems when developers implement suboptimal design solutions due to lack of knowledge and/or time constraints. For example, the God Class anti-pattern refers to the situation in which a class grows rapidly by the addition of new functionalities, when developers break the principle of single responsibility. Prior empirical studies highlighted the negative impact of anti-patterns on a variety of quality characteristics, such as program comprehension \cite{Ball1999}, maintainability \cite{McCallum2005}, and correctness (increase of fault-proneness) \cite{Lee1999}. Thus, it is important to identify their occurrences in systems and apply refactoring operations to remove them.

Several approaches have been proposed to detect the occurrences of anti-patterns in systems. Most of these approaches attempt to identify bad motifs in models of source code using manually-defined heuristics that rely on some metrics (e.g., cyclomatic complexity). For example, Moha et al. \cite{Moha2014} proposed a domain-specific language to describe and generate detection algorithms for anti-patterns using structural and lexical metrics while Palomba et al. \cite{Palomba2016, Palomba2018} proposed a rule-based approach to detect anti-patterns from change history information.

Even though these approaches have shown acceptable performances, none of them can claim high accuracy on any systems and for any anti-patterns. Besides, each approach relies on its own definitions of anti-patterns and only focuses on specific aspects of systems. Thus, we observe a complementarity among the different approaches, especially when they rely on orthogonal sources of information (e.g., structural vs. historical) \cite{Ghose2018, Palomba2018}.

Consequently, we propose SMAD (SMart Aggregation of Anti-patterns Detectors), a machine-learning based ensemble method to combine various anti-patterns detection approaches in order to achieve better performances. For each approach to be aggregated, we identify a set of core metrics, i.e., metrics that reflect the internal detection rule of the approach. We then use the core metrics as input features of a neural-network classifier. To the best of our knowledge, we are the first to propose an ensemble method in the context of anti-patterns detection.

Recently, machine-learning models have been shown efficient in a variety of domains, such as speech recognition \cite{Hinton2012} or image processing \cite{Krizhevsky2012}. Several machine-learning based approaches have been proposed to detect anti-patterns. However, these approaches failed to surpass clearly conventional techniques. On the one hand, learning high-level features of systems requires com-
plex machine-learning models, such as deep-neural-networks. On the other hand, these complex models require substantial amounts of manually-produced training data, which is hardly available and time consuming to produce for anti-patterns.

On the contrary our method relies on existing approaches which allow our model to take as input a low number of high-level key features (i.e., the core metrics). As a consequence, our method can benefit from a simple machine-learning classifier that requires a reasonable number of training examples. This characteristic allows us to consider using our method to label systems’ instances for training other complex detection models. Indeed, in a typical scenario, a training dataset is built by performing a manual validation over the occurrences detected by multiple approaches [11]. Hence, SMAD can be used to automate this process and automatically label training data from a reasonable number of manually-defined examples.

We implemented the proposed ensemble method to detect two well known anti-patterns: God Class and Feature Envy. To conduct our experiments, we created an oracle containing occurrences of the studied anti-patterns in eight Java systems. We used instances from five of the eight systems to train the proposed model and the remaining instances for evaluation.

This paper thus makes the following contributions: (1) a manually-produced oracle reporting the occurrences of God Class and Feature Envy in eight Java software systems; (2) a machine learning-based ensemble method to aggregate existing anti-patterns detection approaches; and (3) a process for the automatic generation of training data for machine-learning based anti-patterns detection models.

The remainder of this paper is organized as follows. Section 2 defines the two anti-patterns considered in this study and discusses the related work. Section 3 describes our approach SMAD. Section 4 presents our data as well as preliminary considerations for our study. Sections 5 reports the results of our first study aiming to evaluate the performances of our method, while Section 6 presents the results of our second study which assesses the ability of SMAD to label training data. Section 7 discusses the threats that could affect the validity of our results. Finally, Section 8 concludes with future work.

2. Background and Related Work

This section defines the anti-patterns considered in this study and discusses prior detection approaches proposed in literature, as well as ensemble methods.

2.1. Definitions

2.1.1. God Class

A God Class or Blob, is a class that tends to centralize most of the system’s intelligence, and implements a high number of responsibilities. It is characterized by the presence of a large number of attributes, methods and dependencies with data classes (i.e., classes only used to store data in the form of attributes that can be accessed via getters and setters). Thus, assigning much of the work to a single class, delegating only minor operations to other small classes causes a negative impact on program comprehension [11] and reusability. The alternative refactoring operation commonly applied to remove this anti-pattern is called Extract Class Refactoring and consists in splitting the affected God Class into several more cohesive smaller classes [12].

2.1.2. Feature Envy

A method that is more interested in the data of another class (the envied class) than that of the class it is actually in. This anti-pattern represents a symptom of the method’s misplacement, and is characterized by a lot of accesses to foreign attributes and methods. The main consequences are an increase of coupling and a reduction of cohesion, because the affected method often implements responsibilities more related to the envied class with respect to the methods of its own class. This anti-pattern is commonly removed using Move Method Refactoring, which consists in moving all or parts of the affected method to the envied class [12].

2.2. Rule Based Approaches

The first attempts to detect components affected by anti-patterns have focused on the definition of rule-based approaches which rely on some metrics to capture deviations from good object-oriented design principles. First, Marinescu [27] presented detection strategy, a metric-based mechanism for analyzing source code models and detect design fragments. They illustrate this methodology step by step by defining the detection strategy for God Class. Later, Lanza and Marinescu [22] formulated the detection strategies for 11 anti-patterns by designing a set of metrics, along with thresholds, for each anti-pattern. These metric–threshold pairs are then logically combined using AND/OR operators to create the final detection rule. These heuristics have been implemented inside Eclipse plug-ins such as InCode [28].

Similar to the approach described above, Moha et al. [30] proposed DECOR (DEtection and CORrection of Design Flaws) which relies on a systematic analysis of the definitions of code and design smells in the literature. They propose templates and a grammar to encode these smells and generate detection algorithms automatically. They applied their approach to four design anti-patterns (God Class, Functional Decomposition, Spaghetti Code, and Swiss Army Knife) and their 15 underlying code smells. Their detection approach takes the form of a “Rule Card” that encodes the formal definition of design anti-patterns and code smells. In this context, the identification of components affected by a God Class is based on both structural and lexical information.

Other approaches rely on the identification of refactoring opportunities to detect anti-patterns. Based on this consideration, instances of a given anti-pattern can be detected in a system by looking at the opportunities to apply the corresponding refactoring operation. In this context, Fokaefs et al. [9] proposed an approach
to detect God Classes in a system by suggesting a set of Extract Class Refactoring operations. This set of refactoring opportunities is generated in two main steps. First, they identify cohesive clusters of entities (i.e., attributes and methods) in each class of the system, that could then be extracted as separate classes. To do so, the Jaccard distance is computed among each class members (i.e., entities). The Jaccard distance between two entities \( e_i \) and \( e_j \) measures the dissimilarity between their respective “entity sets” \( S_i \) and \( S_j \) and is computed as follows:

\[
dist(e_i, e_j) = 1 - \frac{|S_i \cap S_j|}{|S_i \cup S_j|}
\]  

(1)

For a method, the “entity set” contains the entities accessed by the method, and for an attribute, it contains the methods accessing this attribute. Then, cohesive groups of entities are identified using a hierarchical agglomerative algorithm on the information previously generated. In the second step, the potential classes to be extracted are filtered using a set of rules, to ensure that the behavior of the original program is preserved. Later, this approach has been implemented as an Eclipse plug-in called JDeodorant.

Similarly, methods that can potentially be moved to another class are presented to the software engineer as potential Feature Envy methods. In this context, Tsantalis and Chatzigeorgiou proposed an approach for automatic suggestions of Move Method Refactoring. First, for each method \( m \) in the system, a set of candidate target classes \( T \) is created by examining the entities that are accessed in the body of \( m \). Second, \( T \) is sorted according to two criteria: (1) the number of entities that \( m \) accesses from each target class of \( T \) in descending order and; (2) the Jaccard distance from \( m \) to each target class in ascending order if \( m \) accesses an equal number of entities from two or more classes. In this context, the Jaccard distance between an entity \( e \) and a class \( C \) is computed as follows:

\[
dist(e, C) = 1 - \frac{|S_e \cap S_C|}{|S_e \cup S_C|} \quad \text{where} \quad S_C = \bigcup_{e \in C} |e|
\]  

(2)

With \( S_e \) the entity set of a method defined in Equation 1. Third, \( T \) is filtered under the condition that \( m \) must modify at least one data structure in the target class. Fourth, they suggest to move \( m \) to the first target class in \( T \) that satisfies a set of preconditions related to compilation, behavior, and quality. This algorithm is also implemented in the Eclipse plug-in JDeodorant.

Anti-patterns can also impact how source code entities evolve with one another over time, when changes are applied to the system. Based on such consideration, Palomba et al. proposed HIST (Historical Information for Smell deTecTion), an approach to detect anti-patterns using historical information derived from version control systems (e.g., Git, SVN). They applied their approach to the detection of five anti-patterns: Divergent Change, Shotgun Surgery, Parallel Inheritance, God Class and Feature Envy. The detection process followed by HIST consists of two steps. First, historical information is extracted from versioning systems using a component called the change history extractor which outputs the sequence of changes applied to source code entities (i.e., classes or methods) through the history of the system. Second, a set of rules is applied to this so produced sequence to identify occurrences of anti-patterns. For instance, Feature Envy methods are identified as those “involved in commits with methods of another class of the system \( \beta \% \) more than in commits with methods of their class”. The value of \( \beta \) being set to 80% after parameters calibration.

2.3. Machine Learning Based Approaches

Kreimer proposed the use of decision trees to identify occurrences of God Class and Long Method. Their model relies on the number of fields, number of methods, and number of statements as decision criteria for God Class detection and have been evaluated on two small systems (IYC and WEKA). This observation has been confirmed 10 years later by Amorim et al. who extended this approach to 12 anti-patterns.

Khomh et al. presented BDTEx (Bayesian Detection Expert), a metric based approach to build Bayesian Belief Networks from the definitions of anti-patterns. This approach has been validated on three different anti-patterns (God Class, Functional Decomposition, and Spaghetti Code) and provides a probability that a given entity is affected instead of a boolean value like other approaches. Following, Vaucher et al. relied on Bayesian Belief Networks to track the evolution of the “godliness” of a class and thus, distinguishing real God Classes from those that are so by design.

Maiga et al. introduced SVMDetect, an approach based on Support Vector Machines to detect four well known anti-patterns: God Class, Functional Decomposition, Spaghetti code, and Swiss Army Knife. The input vector fed into their classifier for God Class detection is composed of 60 structural metrics computed using the PADL meta-model.

Fontana et al. performed the largest experiment on the effectiveness of machine learning algorithms for smell detection. They conducted a study where 16 different machine learning algorithms were implemented (along with their boosting variant) for the detection of four smells (Data Class, God Class, Feature Envy, and Long Method) on 74 software systems belonging to the Qualitas Corpus dataset. The experiments have been conducted using a set of independent metrics related to class, method, package and project level as input information and the datasets used for training and evaluation have been filtered using an under-sampling technique (i.e., instances have been removed from the original dataset) to avoid the poor performances commonly reported from machine learning models on imbalanced datasets. Their study concluded that the algorithm that performed the best for both God Class and Feature Envy was the J48 decision tree algorithm with an F-measure close to 100%. However, Di Nucci et
al. [6] replicated their study and highlighted many limitations. In particular, the way the datasets used in this study have been constructed is strongly discussed and the performances achieved after replication were far from those originally reported.

More recently, Liu et al. [23] proposed a deep learning based approach to detect Feature Envy. Their approach relies on both structural and lexical information. On one side, the names of the method, the enclosing class (i.e., where the method is implemented) and the envied class are fed into convolutional layers. On the other side, the distance presented in Equation 2 is computed for both the enclosing class $(dist(m, ec))$ and the target class $(dist(m, tc))$, and values are fed into other convolutional layers. Then the output of both sides is fed into fully-connected layers to perform classification. To train and evaluate their model, they use an approach similar to Moghadam and O’Cinnéide [29] where labeled samples are automatically generated from open-source applications by the injection of affected methods. These methods assumed to be correctly placed in the original systems are extracted and moved into random classes to produce artificial Feature Envy occurrences (i.e., misplaced methods).

2.4. Ensemble Methods

Ensemble methods aim at aggregating multiple classifiers in order to improve the classification performances. Ensemble methods are commonly used in the literature as Boosting techniques [35], i.e., a function is applied to the output of various machine-learning based classifiers trained independently. We found no existing ensemble method proposed for anti-patterns detection, as most of the existing detection approaches rely on manually defined rules. However, two ensemble methods proposed in the context of Bug prediction can be applied to our problem.

First, Liu et al. [24] proposed Validation and Voting, which consists in considering a majority vote over the outputs of the classifiers. Second, Di Nucci et al. [5] proposed ASCI (Adaptive Selection of Classifiers in bug prediction), an adaptive method which uses a decision tree algorithm to dynamically predict which classifier is the best for each code component to be classified. The workflow of ASCI is organised as follows: Given a training set $T$ of instances (i.e., code components) and their associated labels (i.e., buggy or not buggy), each classifier is experimented against $T$. Then a new training set $T^*$ is created by labelling each input instance with the information about the classifier which correctly identified its bug-proneness. Then a decision tree is trained on $T^*$ to predict the best classifier for each input instance.

3. SMAD: SMart Aggregation of Anti-patterns Detectors

3.1. Problem Definition

Let us consider $D$ anti-patterns detection tools $d_1, d_2, ..., d_D$ performing a boolean prediction over the entities (i.e., classes or methods) of a software system based on some internal detection rule. We refer to as $d_i(e)$ the boolean prediction of the $i$-th detection tool on an entity $e$.

We want to combine these approaches to maximize the F-measure (cf. Equation 5) of the so-produced “merged” prediction over the entities of the studied system. Thus, we want to find a function of the $D$ approaches that outputs an improved prediction on any software system $S$. Which can be expressed as:

$$f(d_1, d_2, ..., d_D, e) \in \{True, False\}$$

and

$$F_m(f(d_1, d_2, ..., d_D, S)) \geq \max_i F_m(d_i(S)), \ \forall S$$

3.2. Overview

The proposed method SMAD allows to combine various detection approaches on the basis of their internal detection rule instead of their output. Indeed, the internal detection process of any rule based approach relies on some structural or historical metrics (i.e., core-metrics) that can be computed for any entity to be classified. Thus, the key idea behind SMAD is to compute the core-metrics of various approaches for each input entity and use these metrics to feed a machine-learning based classifier. First, for each anti-pattern considered in this study, we selected three state-of-the-art detection tools to be aggregated. These tools respectively rely on:

- **Rule Cards**: Affected entities are identified using a combination of source-code metrics designed to reflect the formal definition of the anti-patterns. For this category, we selected DECOR [30] for God Class and InCode [28] for Feature Envy detection.
- **Historical Information**: Affected entities are identified via an analysis of change history information derived from versioning systems. For this category, we used HIST [32, 31] for both God Class and Feature Envy detection.
- **Refactoring Opportunities**: Anti-patterns are detected by identifying the opportunities to apply their corresponding refactoring operations. For this category, we used the refactoring operations Extract Class [9] and Move Method [41] provided by JDeodorant, respectively for God Class and Feature Envy detection.

Selecting tools that are based on different strategies allows us to expect a high complementarity of the aggregated approaches and thus, maximize the expected performances of our method. Then, we selected the core metrics, i.e., metrics that reflect best the internal decision process of each tool, as input features for our model. The classifier used in SMAD to predict whether an entity is an anti-pattern or not is a Multi-layer Perceptron, i.e., a fully-connected feed-forward neural-network. This model is composed of $\tanh$ dense hidden layers connected to a $softmax$ output layer. Fig. [4] Overview our approach.
3.3. Input

3.3.1. Metrics for God Class Detection

For God Class detection, we extract six core metrics from the three detection tools considered in this study. These metrics are computed for each class of a system.

**DECOR:** The internal detection rule relies on the definition of four code and design smells and can be expressed as: “(is associated to many DataClass) AND is a (ControllerClass OR LargeClass OR LowCohesionClass)”. These smells are defined using structural and lexical metrics along with some thresholds: (1) DataClass relies on the number of accessors, (2) ControllerClass relies on lexical properties, (3) LargeClass relies on the sum of the NMD and NAD metrics (Number of Methods Declared + Number of Attributes Declared), and (4) LowCohesionClass relies on the LCOM metric (Lack of Cohesion in Methods) [4]. Thus, we extracted four core metrics from DECOR internal detection rule for God Class:

- Number of associated DataClass
- ControllerClass
- nmd nad
- lcom

with nmd nad and lcom being the uppercase metrics divided by their respective threshold. The value of these thresholds depends on the systems characteristics and can be computed through the Ptidej API.\(^1\)

**HIST:** God Classes are identified as: “classes modified (in any way) in more than \(a\)% of commits involving at least another class”. Thus, we extracted one core metric from HIST internal detection rule for God Class:

- Number of commits in which the considered class has been modified along with other classes.

**JDeodorant:** God Classes are classes from which a concept (i.e., a subclass) can be extracted. Formally, a concept is defined as: “a distinct entity or abstraction for which a single class provides a description and/or a set of attributes and methods that contribute together to the same task”. We define our core metric for JDeodorant as:

- Number of concepts that can be extracted from the considered class.

3.3.2. Metrics for Feature Envy Detection

A Feature Envy is characterized by two source code components: a method (i.e., the envious method) and a class (i.e., the envied class). Thus, in a given system, the number of potential entities that must be investigated is equal to \(n_m \times (n_c - 1)\) with \(n_c\) and \(n_m\) respectively the numbers of classes and methods in the system.

To reduce this number, we filter the studied system at both class and method level, similarly to Tsantalis and Chatzigeorgiou [41]. First, we consider as potential envious methods only non-static and non-accessor methods. Then, for each of the remaining methods, we consider as potential envied classes only classes that are accessed in some way in the body of the method. We extract seven core metrics from the three considered detection tools.

**InCode:** Methods are identified as being envious without information about the envied class. In this context, a method is declared affected if: (1) “it uses directly more than a few attributes of other classes” (ATFD > FEW), (2) “it uses far more attributes from other classes than its own” (LAA < ONE THIRD), and (3) “the used “foreign” attributes belong to very few other classes” (FDP ≤ FEW). We redefined the first two metrics to express information about the envied class, which led us to three core metrics:

- ATFD (Access To Foreign Data), i.e., number of attributes of the envied class accessed by the method.
- LAA (Locality of Attribute Accesses), i.e., ratio between the number of accesses to attributes that belongs to the envied class vs. the enclosing class.
- FDP (Foreign Data Providers), i.e., number of distinct foreign classes whose attributes are accessed by the method.

\(^1\)https://github.com/ptidejteam/v5.2
3.4. Replication Package

To facilitate further evaluation and reuse of our work, all the data used in this study is publicly available.

Our replication package includes: (1) the oracle; (2) the source code of our model; (3) the scripts used to generate our data; and, (4) the implementation of our experiments. Furthermore, we created a component called repositoryMiner to extract automatically all the necessary data to test or train our model on new systems.

4. Methodology

This section describes the data used to run our experiments, the metrics used to assess the performances of the different approaches investigated in this work, as well as the methodology used for training neural-networks to detect anti-patterns.

4.1. Building a Reliable Oracle

To train and evaluate the performances of SMAD, we needed an oracle reporting the occurrences of the two studied anti-patterns in a set of software systems. We found no such large dataset in the literature. One existing crowd-sourcing dataset, Landfill \cite{Landfill}, included manually-tagged anti-pattern occurrences but we found many erroneously-tagged instances, which discouraged and prevented its use in our work.

For God Class, we found two sets of manually-detected occurrences in open-source Java systems, respectively from DECOR \cite{DECOR} and HIST \cite{HIST} replication packages. Thus, we created our oracle from these sets under two constraints: (1) the full history of the system must be available through Git or SVN, and (2) the occurrences reported must be relevant, i.e., we kept only the systems for which we agreed with the occurrences tagged. After filtering, over the 15 systems available in these replication packages, we retained eight to construct our oracle.

For Feature Envy, most of the approaches proposed in the literature are evaluated on artificial occurrences, i.e., methods assumed to be correctly placed in the original systems, are then extracted and moved into random classes to produce Feature Envy occurrences (i.e., misplaced methods) \cite{FeatureEnvy}. However, our approach partially relies on the history of code components. Therefore, such artificial occurrences are not usable because they have been willingly introduced in the considered systems’ snapshot. Thus, we had to build manually our own oracle.

First, we formed a set of 779 candidate Feature Envy occurrences over the eight subject systems by merging the output of three detection tools (HIST, InCode, and JDeodorant), adjusting their detection thresholds to produce a number of candidate per system proportional to the systems sizes. Second, three different groups of people manually checked each candidate of this set: (1) the authors of this paper, (2) nine M.Sc. and Ph.D. students, and (3) two software engineers. We gave them access to the source code of the enclosing classes (where the methods were defined) and the potential envied classes. After analyzing each candidate, we asked respondents to report their confidence in the range \{strongly approve, weakly approve, weakly disapprove, strongly disapprove\}. To avoid any bias, none of the respondent was aware of the origin of each candidate. We made the final decision using a weighted vote over the reported answers. First we assigned the following weights to each confidence level:

\[
\begin{align*}
\text{strongly approve} & \rightarrow 1.00 \\
\text{weakly approve} & \rightarrow 0.66 \\
\text{weakly disapprove} & \rightarrow 0.33 \\
\text{strongly disapprove} & \rightarrow 0.00 
\end{align*}
\]

\footnote{\url{https://github.com/antoineBarbez/SMAD/}}
Then, a candidate is considered as a Feature Envy if the mean weight of the three answers reported for this occurrence is greater than 0.5.

Table 1 reports, for each system, the number of God Classes, the number of produced Feature Envy candidates, and the number of Feature Envy retained after manual-checking.

Table 1: Characteristics of the Oracle

| System name              | #God CLASS | #Candidate_FE | #Feature_Envy |
|--------------------------|------------|---------------|---------------|
| Android Opt Telephony    | 11         | 62            | 18            |
| Android Support          | 4          | 21            | 2             |
| Apache Ant               | 7          | 110           | 25            |
| Apache Tomcat            | 5          | 173           | 57            |
| Apache Lucene            | 4          | 42            | 4             |
| ArgoUML                  | 22         | 144           | 24            |
| Jedit                    | 5          | 98            | 22            |
| Xerces                   | 15         | 129           | 37            |
| Total                    | 73         | 779           | 189           |

4.2. Studied Systems

The context of our study consists of the eight open-source Java software systems presented in Table 1, which belong to various ecosystems. Two systems belong to the Android API[^4], Android Opt Telephony and Android Support. Four systems belong to the Apache Foundation[^5], Apache Ant, Apache Tomcat, Apache Lucene, and Apache Xerces. Finally, one free UML design software: ArgoUML[^6] and one text editor: Jedit[^7] available under GNU General Public License[^8]. Without loss of generalizability, we chose to analyze only the directories that implement the core features of the systems and to ignore test directories. Table 2 reports for each system, the Git identification (SHA) of the considered snapshot, its age (i.e., number of commit) and its size (i.e., number of class).

Table 2: Characteristics of the Studied Systems

| System name              | Snapshot   | Directory   | #Commit | #Class |
|--------------------------|------------|-------------|---------|--------|
| Android Opt Telephony    | e241cad    | src/java/   | 98      | 192    |
| Android Support          | 38ec0cf    | v4/         | 195     | 109    |
| Apache Ant               | c7734de    | src/main/   | 6397    | 694    |
| Apache Tomcat            | 398ca7ee   | java/org/   | 3289    | 925    |
| Apache Lucene            | 39f6dc1    | src/java/   | 429     | 155    |
| Apache Xerces            | c986230    | src/        | 3453    | 512    |
| ArgoUML                  | 6edc166    | src_new/    | 5559    | 1230   |
| Jedit                    | e343491    | /           | 1181    | 423    |

To evaluate and compare the performances of SMAD with those of the competitive approaches, we selected three systems, i.e., Android Support, Apache Tomcat, and Jedit, from the eight available in our oracle to run the different approaches on. We selected these systems to increase the generalizability of our findings. Indeed, they belong to different domains: telephony framework, service container, and text editor and their sizes and history lengths cover the range of possible values as shown in Table 2. We used the remaining five systems to train our model and calibrate hyper-parameters.

4.3. Evaluation Metrics

To compare the performances achieved by different approaches on the studied systems, we consider each approach as a binary classifier able to perform a boolean prediction on each entity of the system. Thus, we evaluate their performances using the following confusion matrix:

Table 3: Confusion Matrix for Anti-patterns Detection

|       | predicted | total |
|-------|-----------|-------|
|       | 1         | 0     |
| true  | A         | B     |
| false | C         | D     |
| total | m_pos     | m_neg |

With (A) the number of true positives, (B) the number of misses, (C) the number of false alarms and (D) the number of true negatives. Then, based on this matrix, we compute the widely adopted precision and recall metrics:

\[
\text{precision} = \frac{A}{A + C} \quad (3) \quad \text{recall} = \frac{A}{A + B} \quad (4)
\]

We also compute the F-measure (i.e., the harmonic mean of precision and recall) to obtain a single aggregated metric:

\[
F_m = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} = 2 \times \frac{A}{n_{pos} + m_{pos}} \quad (5)
\]

4.4. Training

Here, we discuss the considerations adopted to train neural-networks on the task of anti-patterns detection. We consider training a multi-layer feed-forward neural-network to perform a boolean prediction on each entity of the training systems. First, the training set \( D \) contains \( N = 5 \) training systems which can be expressed as:

\[
D = \{S_i\}_{i=1}^N, \quad \text{with} \quad S_i = \{(x_{ij}, y_{ij})\}_{j=1}^{n_i}
\]

With \( S_i \) the \( i \)th training system, \( x_{ij} \) the input vector corresponding to the \( j \)th entity of this system, \( y_{ij} \in \{0, 1\} \) the true label for this entity and \( n_i \) the size (i.e., number of entities) of \( S_i \). Second, we refer to the output of the neural network corresponding to the positive label, i.e., the predicted probability that an entity is affected as: \( P_\theta(1|x_{ij}) \).

[^3]: https://android.googlesource.com/
[^4]: https://www.apache.org/
[^5]: http://argouml.tigris.org/
[^6]: http://www.jedit.org/
[^7]: https://www.gnu.org/
4.4.1. Custom Loss Function

Software systems are usually affected by a small proportion of anti-patterns (< 1%) \[32\]. As a consequence, the distribution of labels within a dataset containing software system entities is highly imbalanced. Such imbalanced dataset compromises the performances of models optimized using conventional loss functions \[15\]. Indeed, the conventional binary cross-entropy loss function maximizes the expected accuracy on a given dataset, i.e., the proportion of instances correctly labeled. In the context of anti-patterns, the use of this loss function lead to useless models that assign the majority label to all input instances, thus maximizing the overall accuracy (> 99%) during training. To overcome this issue, we must define a loss function that reflects our training objective (i.e., maximizing the F-measure achieved over the training systems).

Let us formulate our training objective as finding the set of weights $\theta^*$ that maximizes the mean F-measure achieved over the training system, which can be expressed as:

$$
\theta^* = \arg \max_{\theta} \frac{1}{N} \sum_{i=1}^{N} F_m(\theta, S_i)
$$

(7)

Which is equivalent to the minimization of the empirical risk by considering a loss: $L = -F_m$. However, to solve this problem through gradient descent, we need our loss to be a continuous and differentiable function of the weights $\theta$. As defined in Equation 5, the F-measure does not meet this criterion, which prevents its direct use to define our loss function. Indeed, computing the number of true positives ($A$) and positives ($m_{\text{pos}}$) requires counting elements from the probability outputed by the model, which necessarily involves discontinuous operators:

$$
A(\theta, S_i) = \sum_{j=1}^{n_i} \left[ P_{\theta}(1|x_{ij}) > 0.5 \right]
$$

(8)

$$
m_{\text{pos}}(\theta, S_i) = \sum_{j=1}^{n_i} \left[ P_{\theta}(1|x_{ij}) > 0.5 \right]
$$

(9)

Where:

$$
\|x\| = \begin{cases} 1 & \text{if } x=\text{True} \\ 0 & \text{if } x=\text{False} \end{cases}
$$

Consequently, we use the differentiable approximation of the F-measure provided by Jansche \[16\], which simply consists in considering:

$$
\left[ P_{\theta}(1|x_{ij}) > 0.5 \right] \approx P_{\theta}(1|x_{ij})
$$

(10)

Thus, the approximated F-measure can be expressed as:

$$
\tilde{F}_m(\theta, S_i) = 2 \times \frac{\tilde{A}(\theta, S_i)}{n_{\text{pos}} + \tilde{m}_{\text{pos}}(\theta, S_i)}
$$

(11)

Where:

$$
\tilde{A}(\theta, S_i) = \sum_{j=1}^{n_i} P_{\theta}(1|x_{ij})
$$

(12)

$$
\tilde{m}_{\text{pos}}(\theta, S_i) = \sum_{j=1}^{n_i} P_{\theta}(1|x_{ij})
$$

(13)

Finally, we define our loss function as follows:

$$
L = -\tilde{F}_m(\theta, S_i)
$$

(14)

4.4.2. Regularization

Regularization is a way to prevent over-fitting. We used two widely-adopted regularization techniques: $L_2$ regularization and dropout.

$L_2$ Regularization: $L_2$ regularization consists in adding a term to the loss function to encourage the weights to be small \[44\]. This term is proportional to the sum of the Euclidean norm of the weight matrices, i.e., $\|W\|_2 = \sqrt{\sum_{i} W_i^T W_i}$, also called $L_2$-norm. Thus, the $L_2$ regularization term added to the loss function can be expressed as:

$$
L_2 = \lambda \sum_{l=1}^{L+1} \| W_l \|_2
$$

(15)

With $\lambda \in \mathbb{R}$ an hyper-parameter adjusted during cross-validation and $L$ the number of hidden layers in the network.

Dropout: Dropout consists in dropping randomly out units, i.e., temporarily removing nodes of the network along with their connections during training. Thus, at each step, each node has a probability $(1 - P_{\text{keep}})$ to be removed from the network. Dropout is equivalent to combining exponentially many architectures with shared parameters and has proved to prevent successfully over-fitting \[38\].

5. Evaluation of the Detection Performances

In this section, we address the evaluation of SMAD performances in detecting the two anti-patterns considered in this study. We answer the two following research questions:

• **RQ1:** Does SMAD outperform standalone detection tools?

• **RQ2:** Does SMAD outperform other ensemble methods?
5.1. Study Design

The goal of this study is to evaluate the proposed ensemble method on both God Class and Feature Envy. We compare SMAD to the standalone detection tools aggregated through our approach as well as to other ensemble methods. As explained in Section 4.2, we assess the performances of the respective approaches on three systems (i.e., Android Support, Apache Tomcat, and Jedit) while keeping the other five for training and/or parameters tuning.

To run the standalone tools on the evaluation systems (RQ1), we used their publicly-available implementations whenever possible and replicated the approaches for which no implementation was available. Thus, we ran DECOR using the Ptridge API and JDeodorant using its Eclipse plug-in. We implemented the detection rules for HIST as described in its original paper [33]. InCode Eclipse plug-in is no longer available and we re-implemented its detection rule as described in the original book [22] to retrieve also information about the envied class, as explained in Section 3.3.2.

To answer RQ2, we choose to compare SMAD to the voting technique and the method ASCI proposed by Di Nucci et al. [5]. We selected these two techniques because, to the best of our knowledge, other ensemble methods are specific to machine-learning classifiers. Furthermore, these two techniques have been shown to achieve state-of-the-art results in the context of bug prediction [13, 24, 5]. The voting technique predicts an entity as affected if it has been detected by at least k classifiers. We call k the policy of the vote. This parameter has been tuned before conducting our experiments, contrary to the Validation and Voting method proposed by Liu et al. [24], which uses a majority voting policy (k = 2 in our case). The ASCI method uses a decision tree algorithm to predict the best classifier for each entity given its characteristics. Then, an entity is declared as affected according to the classifier selected by ASCI for this entity. Regarding the input of the decision tree, i.e., the characteristics of the entities, we used the same metrics used for SMAD and presented in Section 3.3.

5.2. Parameters Calibration

5.2.1. SMAD

To calibrate the hyper-parameters of our model, we performed a random search over 300 generations of five hyper-parameters: learning rate (η), λ, Pkeep, number of hidden layers, and number of neurons per hidden layer. This technique has shown to be more efficient than grid search on similar multi-dimensional optimization problems [3]. We evaluated the performances achieved on each hyper-parameters’ combination by carrying out a 5-fold cross-validation, i.e., leave-one-out, over the five systems contained in our training set: Android Opt Telephony, Apache Ant, Apache Lucene, ArgoUML, and Xerces. At each iteration, we trained five times our model on 100 epochs by leaving one system out to perform the evaluation while keeping the others for training. Table 4 reports, for each hyper-parameter, the range of values experimented as well as the value with the best result for both God Class and Feature Envy.

Finally, the two models used for experiments (i.e., one model per anti-pattern) have been trained on 400 epochs with an exponential learning rate decay of 0.7 every 100 epochs.

Table 4: Hyper-parameters Calibration of SMAD

| Hyper-parameter       | Range     | Best (GC) | Best (FE) |
|-----------------------|-----------|-----------|-----------|
| Learning Rate (η)     | 10−0.8;1  | 8.26×10−5 | 1.90×10−4 |
| L2-norm (λ)           | 10−2;1.5  | 3.13×10−2 | 1.97×10−3 |
| Dropout (Pkeep)       | 0.5;1.0   | 0.5       | 1.0       |
| Number of Hidden Layers | 1;3    | 2         | 2         |
| Neurons per Layer     | [4;140]   | [34, 30]  | [86, 44]  |

With n the size of the previous hidden layer.

5.2.2. Detection Tools

Although we followed rigorously the guidelines given by the authors of HIST and InCode when reimplementing these tools, some differences may remain between our respective implementations. Such differences could affect the optimal values of their parameters. Thus, we performed an additional parameter tuning for these tools by computing the mean F-measure achieved over the eight systems considered in this study. We retained values that led to the best performances in our experiments. Table 5 reports, for each investigated parameter, the range of values experimented and the value retained to conduct our experiments.

Table 5: Hyper-parameters Calibration of the Competitive Tools

| Tool       | Hyper-parameter(s) | Range                | Best Value |
|------------|--------------------|----------------------|------------|
| HIST (FE)  | α                  | From 0% to 100%     | 160%       |
| HIST (GC)  | β                  | From 0% to 20%      | 8%         |
| InCode     | (ATFD, LAA, FDP)   | [0; 7]               | (2, 3, 3)  |

5.3. Analysis of the Results

Table 6 reports the results of our experiments for God Class while Table 7 reports our results for Feature Envy. Our results report the performances on the three subject systems, in terms of precision, recall, and F-measure, achieved by: (1) the three detection tools used for aggregation; (2) two competitive ensemble methods: Vote and ASCI; and, (3) SMAD. In addition, we report the mean values of the three performance metrics for each investigated approaches.

5.3.1. Does SMAD outperform standalone detection tools?

For God Class detection, SMAD shows a precision of 74% and a recall of 63% (F-measure of 66%) on average over the subject systems. Thus, the proposed ensemble method clearly outperforms the three approaches used for aggregation. Specifically,
the mean F-measure improves by 74% in comparison to the tool that performed the best (HIST with 38%). Considering the performances achieved on each system, SMAD shows an F-measure ranging between 50% and 80%, which confirms that SMAD performs well independently of the systems characteristics. On the contrary, each competitive tool shows poor performances on at least one system. However, the low performances achieved by JDeodorant (especially precision) can be due to this tool relying on a different definition of God Class than others. Indeed, affected entities are detected only if opportunities to split them are identified.

For Feature Envy detection, SMAD achieves on average a precision of 74% and a recall of 67% leading to an F-measure of 70%. We observe better performances in terms of F-measure achieved by the static code analysis tools (52% by InCode and 50% by JDeodorant) than for God Class detection and low results for HIST. These results show that SMAD outperforms standalone tools when detecting Feature Envy with a mean F-measure 35% higher than that of the tool that performed the best (InCode with 52%). However, when replicating HIST rules for Feature Envy detection, we used a different component\footnote{http://www.incava.org/projects/diff} to extract changes at method level than that of the original approach because the original component is supposedly unavailable because of its license. We are aware that such difference could affect the reported performances.

**SMAD significantly outperforms the standalone detection tools in detecting God Class and Feature Envy. Furthermore, our results indicate that SMAD performs well independently of the systems characteristics.**

### 5.3.2 Does SMAD outperform other ensemble methods?

We report the results of our study for both God Class and Feature Envy, considering precision, recall, and F-measure independently in turn. In term of precision, our results indicate that SMAD outperforms both the voting technique and ACSI, with the lowest performances achieved by the voting technique for Feature Envy detection. Indeed, in this case the union vote policy (k=1) predicts an entity as affected if it has been detected by at least one of the three tools. In term of recall, we see that ACSI achieves slightly better performances (65% vs. 63%) than SMAD for God Class, while for Feature Envy, unsurprisingly the union vote policy achieves the highest recall (100%). Finally, in term of F-measure, we see a clear hierarchy among the different ensemble methods. First, the voting technique achieves reasonable performances but does not succeed to outperform the best standalone detection approach. On the contrary, ACSI is able enhance the mean F-measure for both God Class and Feature Envy detection with respectively an improvement of 29% and 2% with respect to the tool that performed the best. Finally, SMAD clearly outperforms the two competitive ensemble methods with an F-measure

Table 6: Performances for God Class detection

| Approaches     | Apache Tomcat | JEdit | Android Platform Support | Mean |
|----------------|---------------|-------|--------------------------|------|
|                | Precision     | Recall | F-measure | Precision | Recall | F-measure | Precision | Recall | F-measure | Precision | Recall | F-measure |
| DECOR          | 67%           | 40%   | 50%        | 17%       | 60%   | 26%       | 0%        | 0%     | 0%        | 28%       | 33%   | 25%       |
| HIST           | 0%            | 0%    | 0%         | 22%       | 40%   | 29%       | 100%      | 75%    | 86%       | 41%       | 38%   | 38%       |
| JDeodorant     | 2%            | 60%   | 4%         | 5%        | 60%   | 9%        | 17%       | 25%    | 20%       | 8%        | 48%   | 11%       |
| Vote (k=2)     | 100%          | 20%   | 33%        | 13%       | 40%   | 20%       | 100%      | 25%    | 40%       | 71%       | 28%   | 31%       |
| ASCI           | 17%           | 40%   | 24%        | 25%       | 80%   | 38%       | 100%      | 75%    | 85%       | 47%       | 65%   | 49%       |
| SMAD           | 43%           | 60%   | 50%        | 80%       | 80%   | 80%       | 100%      | 50%    | 67%       | 74%       | 63%   | 66%       |

Table 7: Performances for Feature Envy detection

| Approaches     | Apache Tomcat | JEdit | Android Platform Support | Mean |
|----------------|---------------|-------|--------------------------|------|
|                | Precision     | Recall | F-measure | Precision | Recall | F-measure | Precision | Recall | F-measure | Precision | Recall | F-measure |
| InCode         | 52%           | 56%   | 54%        | 46%       | 59%   | 52%       | 50%       | 50%    | 50%       | 49%       | 55%   | 52%       |
| HIST           | 9%            | 9%    | 9%         | 2%        | 5%    | 3%        | 0%        | 0%     | 0%        | 4%        | 4%    | 4%        |
| JDeodorant     | 31%           | 42%   | 36%        | 44%       | 50%   | 47%       | 100%      | 50%    | 67%       | 59%       | 47%   | 50%       |
| Vote (k=1)     | 30%           | 100%  | 46%        | 24%       | 100%  | 39%       | 29%       | 100%   | 44%       | 28%       | 100%  | 43%       |
| ASCI           | 53%           | 33%   | 41%        | 59%       | 45%   | 51%       | 100%      | 50%    | 67%       | 71%       | 43%   | 53%       |
| SMAD           | 52%           | 51%   | 51%        | 69%       | 50%   | 58%       | 100%      | 100%   | 100%      | 74%       | 67%   | 70%       |
improving from 49% to 66% for God Class and from 53% to 70% for Feature Envy in comparison with the best competitive method (i.e., ASCI).

SMAD significantly outperforms other ensemble methods on both God Class and Feature Envy detection. Our results indicate that the voting technique is not suitable to improve the F-measure contrary to ASCI.

6. Evaluation of the Ability to Label Training Instances

Deep neural networks have led to breakthrough results in a variety of domains. For example, the field of image processing has been completely redefined by the use of deep convolutional neural networks [21, 37, 39]. This success stands on their ability to process high-dimensional raw inputs (e.g., a 128 × 128 RGB image contains 5 × 10^4 real values) by learning to identify key features in the data. However, the field of anti-patterns has not yet benefited from such improvements partly because of the unavailability of the training data.

In a typical scenario [11], a training dataset for anti-patterns is created by following the process presented in Section 4.1. First, a set of candidate anti-pattern occurrences is created by merging the detection results of various detection tools. Then, this data is manually verified to remove eventual false positives. However, complex machine-learning models such as deep neural-networks require large amounts of data to be trained. As a consequence, this procedure is almost impossible to achieve in practice for such models.

On the contrary our method relies on existing approaches which allows our model to take as input a low number of high-level key features (i.e., the core metrics). As a consequence, our method can benefit from a simple machine learning classifier that requires a reasonable number of training examples. Indeed, the results of the previous experiments have shown that instances of five systems are sufficient to train our model and achieve good performances.

Consequently, we propose to integrate SMAD in the process of creating an anti-patterns dataset. Indeed SMAD could be used to automate the process of labelling source code entities from a low number of manually produced data. Thus, this study answers the following research question:

• **RQ3:** To what extent can SMAD be used to label training instances for deep-learning anti-pattern detection models?

6.1. Study Design

This study evaluates the ability of SMAD to label training data for deep-learning anti-pattern detection models. We found no such architecture for the detection of God Class in the literature. Thus, we experiment this process only for the detection of Feature Envy on the Convolutional Neural Network (CNN) proposed by Liu et al. [23]. This study compares the performances achieved by: (1) the studied model trained on “injected smells”, i.e., assuming methods are correctly placed in the original systems, they are moved into random classes to produce artificial Feature Envy occurrences and (2) the studied model trained on instances labeled by SMAD.

To produce labeled instances, we considered using the same systems selected in the original study. However, for some of these systems, historical information is not available through version-control systems, which prevents their use in our study. Thus, we selected eleven Java systems of different sizes and domains from the Qualitas Corpus [40]. Table 8 overviews the characteristics of these systems. Then, we used the architecture of SMAD trained and evaluated in Section 5 to label the instances of these systems.

To compare both approaches, we used the implementation made available by the authors to run the original model and we implemented another version that allow the use of the custom loss function defined in Equation 14 for optimization as well as regularization to address the unbalanced labels produced by SMAD. We assessed the performances of the two models on the same three systems used in our previous experiments.

Table 8: Characteristics of the Systems used to Generate Training Instances

| System name | Snapshot | Directory       | #Commit | #Class |
|-------------|----------|-----------------|---------|--------|
| Apache Derby | c30c7da | java/engine/     | 1338    | 1022   |
| Apache Jena | dc0bf6e6| jena-core/src/main/ | 403     | 686    |
| Apache Jspriki | a3b1041 | src/            | 3993    | 330    |
| Apache Log4j | 7cf64b6 | src/java/       | 734     | 313    |
| Apache Velocity | 23c979d | src/            | 1241    | 164    |
| Javacc | 1b23b61 | src/            | 315     | 155    |
| Jgraphix | 25e9cfc | src/            | 117     | 177    |
| Jgroups | 2d2ec7d | src/            | 3138    | 276    |
| Jhotdraw | 58d8d3f | jhotdraw/7/src/main/ | 503    | 549    |
| Mongodb | b67c9c4 | src/main/       | 909     | 111    |
| Pmd | 6063aaf | pmd/src/main/   | 4656    | 815    |

6.2. Parameters Calibration

We calibrate the hyper-parameters of the subject model using a random search over 100 generations of: η and λ. We evaluate the performances obtained from each hyper-parameters combination by computing the mean F-measure achieved over the five systems used to train SMAD in Section 5. Thereby, we calibrate the model on manually-validated occurrences without using testing data. Table 9 reports for each hyper-parameter, the range explored and the value which led to the highest result.

When performing preliminary experiments, we observed that the model had difficulties to learn from both parts of its input (i.e., lexical and structural) together, thus performing better when trained using only lexical or structural information. Consequently, we pretrain the model during 40 epochs using only the structural part of the input (i.e., the distances) before training it on 40 other epochs with the full input.
Table 9: Hyper-parameters Calibration of the Subject Model

| Hyper-parameter   | Range       | Best Value   |
|-------------------|-------------|--------------|
| Learning Rate ($\eta$) | $10^{-[0.0,4.0]}$ | $1.62 \times 10^{-1}$ |
| L2-norm ($\lambda$) | $10^{-[0.0,4.0]}$ | $1.80 \times 10^{-3}$ |

6.3. Analysis of the Results

Table 10 reports the performances achieved by the two CNNs proposed by Liu et al. [23] on the three systems. The first version (referred as LIU_INJ) has been trained on “injected smells” while the second version (referred as LIU_SMAD) has been trained on instances labeled by SMAD. We also report the mean values of the performance metrics on the systems.

6.3.1. To what extent can SMAD be used to label training instances for deep-learning anti-pattern detection models?

Our results show that the deep-learning model achieves a precision of 22% and a recall of 13% (F-measure of 16%) on average when trained on instances labeled by SMAD. These results confirm that instances labeled by SMAD are more suitable to train this model than injected smells for Feature Envy. Indeed, when trained on injected smells, the model achieves the highest recall but at the expense of its precision, which leads to a low F-measure of 3%.

Some factors could explain the difference between our results and those reported in the literature [23]. First, we evaluate a prediction as correct if and only if both the method AND the envied class are correct, while they evaluate their model on two tasks independently: (1) predicting if a method is associated with Feature Envy (without assessing the correctness of the proposed envied class); (2) recommending a destination (i.e., the envied class) only for the methods correctly detected in the previous step. Second, we use a different implementation to compute the distances between methods and classes.

The CNN proposed by Liu et al. [23] achieves better performances when trained on instances labeled by SMAD than on “injected smells”. This result confirms that SMAD generates reliable instances for deep-learning anti-pattern detection models.

7. Threats to Validity

In this section, we discuss the threats that could affect the validity of our study.

Construct Validity. Threats to construct validity concern the relation between theory and observation. In our context, this could refer to the reliability of the oracle used to train and evaluate the different approaches investigated in this work. Instances of God Class extracted from HIST and DECOR replication packages have been filtered before being incorporated in our oracle. Furthermore, both papers have been awarded by the community, which confirms the quality of the processes conducted to produce these instances. For Feature Envy, we followed a strict blind procedure where each instance has been investigated by three different persons. However, we can not exclude the possibility of some missed occurrences or false positives. Another threat is related to the replication of some of the competitive approaches. We followed rigorously the guidelines provided by the respective authors, and as explained in Section 5.2.2, we performed an additional parameter tuning for each approach. However, some differences may remain between our respective implementations.

Internal Validity. Threats to internal validity concerns all the factors that could have impacted our results. In our context, this could refer to the training procedure presented in Section 4.4. Even though we compared the proposed procedure with conventional techniques while performing preliminary experiments, we did not report the results of our comparisons. Hence, a comparative study of the proposed procedure with conventional optimization approaches would be desirable. Also, we used such procedure along with other regularization techniques while training the model proposed by Liu et al. [23]. Note that these techniques are in fact part of the approach we propose and are necessary to train models on real imbalanced datasets. Another threat is related to choice of the machine-learning based classifier used in our method. We plan to investigate the use of different machine-learning algorithms to perform aggregation.

External Validity. Threats to external validity concern the generalizability of our findings. To reduce this threat, the software systems used for evaluation have been selected for their different domains, origins, sizes and history lengths. However, further evaluation of our models on a larger set of systems would be desirable.

8. Conclusion and Future Work

We proposed SMAD, a machine-learning based ensemble method to aggregate various anti-pattern detection approaches on the basis of their internal detection rule. Our method consists in identifying the core-metrics of each approach to be aggregated and then use these metrics to feed a machine-learning based classifier. To train and evaluate our model, we built an oracle containing the occurrences of God Class and Feature Envy in eight open-source systems. To address the poor performances commonly reported by neural-networks on imbalanced datasets such as our oracle, we
also designed a training procedure allowing to maximize the expected F-measure. Then, we evaluated SMAD on: (1) detecting occurrences of God Class and Feature Envy and (2) its ability to label training instances for deep-learning anti-patterns detection models. Key results of our experiments indicate that:

- SMAD significantly outperforms the standalone tools aggregated through our approach in detecting God Class and Feature Envy and performs well independently of the systems characteristics.

- SMAD outperforms other ensemble methods in terms of precision and F-measure.

- The CNN proposed by Liu et al. [23] achieves better performances when trained on instances labeled by SMAD than on “injected smells”, which confirms that SMAD generates reliable instances for deep-learning anti-patterns detection models.

Future work includes a comparative study of the different machine-learning algorithms that could be used for aggregation. We also plan to extend our approach to the detection of other anti-patterns with a greater number of detection tools.

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