Identifying Self-Admitted Technical Debts with Jitterbug: A Two-step Approach

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Abstract—Keeping track of and managing the self-admitted technical debts (SATDs) is important to maintaining a healthy software project. This requires much time and effort from human experts to identify these SATDs manually. Currently, automated solutions do not have high enough precision and recall in identifying SATDs to fully automate the process. To solve the above problems, we propose a two-step framework called Jitterbug for identifying SATDs by first finding the “easy to find” SATDs automatically with close to 100% precision via a novel pattern recognition technique, then applying machine learning techniques to assist human experts in manually identifying the rest “hard to find” SATDs with reduced human effort. Our simulation studies on ten software projects show that Jitterbug can identify SATDs more efficiently (with less human effort) than the prior state of the art methods.

Index Terms—Technical debt, software engineering, machine learning, pattern recognition.

1 INTRODUCTION

Recently, much research has been focusing on identifying the self-admitted technical debts (SATDs) from source code comments. Keeping track of and managing these SATDs is important to maintaining a healthy software project. What we found in this work is that there are two types of SATDs:

• The “easy to find” SATDs which can be automatically identified without human verification. As an example, the comments containing keywords like “fixme, todo” are almost always related to SATDs.

• The “hard to find” SATDs which only human experts can accurately decide whether they are SATDs or not. As an example, the comment “Modify the system class loader instead - horrible! But it works!” is easy to be classified as an SATD by human experts but remains a hard problem for algorithms.

The most important message we want to convey is:

Do not waste effort on finding the “easy to find” SATDs, focus more on identifying the “hard to find” SATDs.

Current solutions for identifying SATDs do not separate the two types of SATDs and belong to either pattern-based approach or machine learning approach. Researchers exploring pattern-based approaches first manually inspect code comments and label each one as SATD or non-SATD; then manually analyze the labeled items and summarize patterns for SATDs, e.g. if a comment has keywords like “hack, fixme, probably a bug”, then it has a high chance of being related to a SATD. On the other hand, machine learning approaches first train a classification model on the manually labeled comments; then predict the unlabeled comments (usually on a “hold-out” test set so that performance metrics like precision and recall can be calculated) for which comments are related to SATDs. Limitations exist in both approaches:

• Pattern-based approaches require large amounts of human effort in analyzing and summarizing the effective patterns.

• Since not all SATDs are “easy to find”, many of the patterns identified by the pattern-based approaches from some source projects could be ineffective in a new, unseen project.

• Even the state of the art machine learning approaches only have around 74% F1 score [1] and 74% AUC [2] (to which the “easy to find” SATDs contribute much). That means the process cannot be fully automated without human experts checking the algorithms’ decisions and making the final call.

Taking advantage of the two types of SATDs, we address the SATD identification problem in two steps:

• Step 1: identify the “easy to find” SATDs automatically. The comments containing keywords like “fixme, todo” are almost always related to SATDs. This suggests that there exist strong patterns that could be used to identify such “easy to find” SATDs automatically, with very high precision. The key challenge of this step is to automatically identify these strong patterns with close to 100% precision so that human experts do not need to verify the results.

• Step 2: guide human experts to manually read the comments without strong patterns looking for the rest “hard to find” SATDs. The rest “hard to find” SATDs cannot be accurately identified through machine learning algorithms. Human efforts are essential for identifying such SATDs. Therefore the key challenge of this step is to (1) guide the human effort to the comments that most likely contain SATDs; and (2) provide information such as an estimation of the number of undiscovered SATDs to help human experts make trade-off choices like when to stop the process.

As shown in Figure 1, we designed Jitterbug, a two-step framework. Jitterbug first utilizes a novel pattern recognition technique to identify patterns that could yield very high precision (if one comment has the recorded patterns then close to 100% chance it is related to SATDs); then trains machine learning models to guide humans discover SATDs from comments that do not have high precision patterns as well as to estimate the number of SATDs left in the comments. This idea of separating the SATD identification...
problem into two steps provides the following advantages: (1) Mining patterns for Step 1 becomes easy since high recall is no longer a requirement. (2) Human efforts are only spent in Step 2 on the “hard to find” SATDs.

Simulated on the latest labeled SATD dataset from Huang et al. [1], we ask and answer the following research questions.

**RQ1: How to find the strong patterns of the “easy to find” SATDs in Step 1?** First, on 9 training projects, a pattern recognizer named Easy, with fitness function specifically designed to achieve high precision, is applied to identify patterns with higher than 80% precision. Then the identified patterns are used on the holdout project to test the performance. We also conducted a validation study on the ground truth labels provided in the dataset by manually analyzing the comments containing the strong patterns found with Easy but were labeled as Non-SATDs. Interesting findings were discovered during our exploration of this step:

1) **Easy** detects the same set of strong patterns—“todo, fixme, hack, workaround” for every target project.
2) **Easy** achieves close to 100% precision (100% on eight projects and 99% on two projects) on identifying the “easy to find” SATDs. These results are higher than the human-derived set of patterns—“todo, fixme, hack, xxx” from Guo et al. [3] (MAT).
3) **Easy** is even more accurate than human experts in identifying the “easy to find” SATDs since 98% of the conflicting comments, which were labeled as Non-SATDs by human but contain the patterns from Easy, are identified as SATDs in our validation study.
4) Although **Easy** is an algorithm with close to 100% precision and barely any cost (training takes seconds), it alone can only identify 20% to 90% of the SATDs. Thus it is necessary for Step 2 to find the rest “hard to find” SATDs.

**RQ2: How to better find the “hard to find” SATDs with less human effort in Step 2?** After all the “easy to find” SATDs are filtered out, a machine learning model is trained to rank the rest comments. Human oracles are queried for the top rank comments and then those oracles are used to update the machine learning model. As shown in Figure 1, this loop will iterate until the target level of recall has been reached in estimation. The advantage of this strategy, named Hard, is that the information in both source projects and newly labeled data in the target project can be utilized to better direct human effort towards comments that are more likely containing SATDs. Our results show that this strategy finds more SATDs with fewer human oracles than the state-of-the-art supervised learning techniques where only information from the training datasets is utilized. Meanwhile, with an accurate estimation of the number of undiscovered SATDs, human experts are easier to make decisions on whether to spend more time looking for the “hard to find” SATDs or to stop at that point.

**RQ3: Overall how does Jitterbug perform?** With Easy automatically finding the “easy to find” SATDs and Hard guiding the human experts to comments that most likely contain the “hard to find” SATDs, Jitterbug can find more SATDs with less human effort compared to other state of the art methods as well as Easy or Hard alone.

### 1.1 Contributions of this Paper

1) In this paper, we show that there are two types of SATDs: the “easy to find” ones that can be identified without human verification, and the “hard to find” ones that only human can make the final decisions on.
2) A novel two-step framework Jitterbug is proposed to identify the two types of SATDs. This framework first identifies the “easy to find” SATDs automatically with a novel pattern recognition technique, then applies machine learning techniques to
assist human experts in manually identifying the rest “hard to find” SATDs with reduced human effort.

3) A novel pattern recognition technique Easy is presented to find strong patterns with close to 100% precision for the “easy to find” SATDs. Results show that its precision is higher than human’s, thus making it reliable to be applied automatically.

4) A continuous learning framework Hard is shown to outperform other supervised learning models in retrieving the “hard to find” SATDs with less human effort, and also to provide information on how many more SATDs are there to be found.

5) All code and data in this work are available allowing other researchers to replicate, improve, or even refute our findings.

The rest of this paper is structured as follows. Some background and related work is discussed in §2. Our methodology is described in §3. This is followed by the details of the SATD datasets in §4. Details of the experiment (simulation) designs and answers to the research questions are presented in §5. Threats to validity to this work are analyzed in §6. While conclusion and future work are provided in §7.

2 BACKGROUND AND RELATED WORK

2.1 About Technical Debt

When developers cut corners and make haste to rush out code, that code often contains technical debt (TD); i.e. decisions that must be repaid, later on, with further work. Technical debt is like dirt in the gears of software production. As TD accumulates, development becomes harder and slower. Ever since the term technical debt (TD) was first introduced by Cunningham in 1993 [4], it has been found to be a widespread problem in the software industry damaging many aspects of a system including evolvability (how fast we can add new functionality) and maintainability (how well we can keep bugs out of the code) [4, 5, 6].

- In 2012, after interviewing 35 software developer from different projects in different companies, varying both in size and type, Lim et al. [7] found developers generate TD due to factors like increased workload, unrealistic deadline in projects, lack of knowledge, boredom, peer-pressure among developers, unawareness or short-term business goals of stakeholders, and reuse of legacy or third party or open-source code.

- After observing five large scale projects, Wehaibi et al. [8] found that the number of technical debt in a project may be very low (only 3% on average), yet they create a significant amount of defects in the future (and fixing such technical debts are more difficult than regular defects).

- Another study on five software large scale companies revealed that TDs contaminate other parts of a software system and most of the future interests are non-linear in nature with respect to time [9].

- According to the SIG (Software Improvement Group) study of Nugroho et al. [6], a regular mid-level project owes $857,500 in TD and resolving TD has a Return On Investment (ROI) of 15% in seven years.

- Guo et al. [5] also found similar results and concluded that the cost of resolving TD in the future is twice as much as resolving immediately.

- As Ozkaya et al. [10] revealed, technical debt affects multiple aspects of the software development process and is mostly invisible.

Therefore identifying TD has a large impact on software development. However, limited success has been achieved while much research tried to identify TD as part of Code Smells using static code analysis [11, 12, 13, 14, 15]. Static code analysis has a high rate of false alarms while imposing complex and heavy structures for identifying TD [16, 17, 18, 19].

2.2 Identifying Self-Admitted Technical Debt

Recently, much more success has been seen in work on the “self-admitted technical debt” (SATD). Technical debt is often “self-admitted” by the developer in code comments [20], thus making it much easier to find. In 2014, after studying four large scale open-source software projects, Potdar and Shihab [20] concluded that developers intentionally leave traces of TD in their comments (saying things like “hack, fixme, is problematic, this isn’t very solid, probably a bug, hope everything will work, fix this crap”).

2.2.1 Pattern-Based Approaches

Pattern-based approaches [20, 21, 22] consist of three steps: (1) manually inspect code comments and label each one as SATD or non-SATD; (2) manually analyze the labeled items and summarize patterns for SATDs, e.g. if a comment has keywords like “hack, fixme, probably a bug”, then it has a high chance of being related to a SATD; (3) apply the summarized patterns to unlabeled comments to identify SATDs.

Potdar and Shihab’s work was now considered the first pattern-based approach for identifying SATDs. They found 62 distinct keywords for identifying such TD [20] (similar conclusions were made by Faris et al. [21]). In 2015, Maldonado et al. used five open-source projects to manually classify different types of SATD [22] and found:

- SATD mostly contains Requirement Debt and Design Debt in source code comments;
- 75% of the SATD gets removed, but the median lifetime of SATD ranges between 18 to 173 days [23].

Another study tried to find the SATD introducing commits in Github using different features on change level [24]. Instead of using the bag of word approach, a recent study also proposed word embedding as a vectorization technique for identifying SATD [25]. These pattern-based studies focused on identifying keywords in code comments that indicating SATDs and then used those keywords to label comments as SATDs [26].

There are risks and problems to this approach. First, it requires much manual effort from human experts to find those keywords by reading thousands of comments. Second, it is natural to believe that such keywords can vary from projects to projects and will not produce 100% precision and recall but none of the studies used a holdout set to evaluate the precision and recall of using such keywords to identify SATDs.

2.2.2 Machine Learning Approaches

To solve the above mentioned problems, machine learning [27, 28, 29, 30] approaches are proposed for identifying SATDs. These approaches, supervised learning models are trained on labeled SATD datasets to learn the underlying rules of comments admitting TDs. For example, Tan et al. [29, 30] analyzed source code comments using natural language processing to understand programming rules and documentations and indicates comment quality and inconsistency. A similar study was done by Khamsi et al [31]. After analyzing and categorizing comments in source
code. Steidl et al. [32] proposed a machine learning technique that can measure the comment quality according to category. Malik et al. [33] used random forest to understand the lifetime of code comments. A similar study over three open-source projects was also done by Fluri et al. [34]. In 2017, Maldonado et al. [27] successfully identified two types of SATD in 10 open-source projects (average 63% F1 Score) using Natural Language Processing (Max Entropy Stanford Classifier) using only 23% training data. A different approach was introduced by Huang et al. [28] in 2018. Using eight datasets, Huang et al. build a Multinomial Naïve Bayes sub-classifier for each training dataset using information gain as feature selection. By implementing a boosting technique using all those sub-classifiers, they have found an average of 73% F1 scores for all datasets [1]. A recent IDE for Eclipse was also released using this technique for identifying SATD in java projects [28]. More recently, Zampetti et al. [2] reported an average precision of 55%, recall of 57%, and AUC of 0.73 with a deep learning-based approach.

These machine learning models can be a good indicator for which comments are more likely to be related to SATDs. However, with precision ranging from 60% to 85%, it is not reliable to fully automate the process. Human experts are then required to verify every decision the machine learning model made and thus costs a large amount of time and labor but still finding only, say 57% of the SATDs.

2.2.3 Two-Step Approaches

As described in [1] we take a two-step approach to identify SATDs: (1) identify patterns for the “easy to find” SATDs with close to 100% precision and automatically classify comments with the patterns as SATDs (without human verification); (2) then apply machine learning techniques to guide human experts to find the rest “hard to find” SATDs with large amount of time and labor but still finding only, say 57% of the SATDs.

3 METHODOLOGY

As shown in Figure [1] Jitterbug consists of two operators—a pattern recognizer Easy and a continuous learning model Hard. To find all possible strong patterns in Step 1, we featurize the data as term frequency matrix without stemming or stop words removal. This section breakdowns the workflow as shown in Algorithm [1] and introduces the two operators in details.

### Algorithm 1: Pseudo Code for Jitterbug

| Function Jitterbug (X,Y,T,rec,CL) |
|----------------------------------|
| // Extract patterns from training data. |
| 2 patterns ← Easy(X); |
| // Identify the "easy to find" SATDs. |
| 3 TDeasy ← Has_Pattern(Y, patterns); |
| // Remove "easy to find" SATDs from training and test data. |
| 4 Yhard ← Y \ TDeasy; |
| 5 Xhard ← X \ Has_Pattern(X, patterns); |
| // Identify the "hard to find" SATDs. |
| 6 TDbad ← Hard(Xhard, Yhard, T, rec); |
| 7 TD ← TDeasy ∪ TDbad; |
| return TD; |

3.1 Easy

Pattern Recognition is an engineering application of Machine Learning. Machine Learning deals with the construction and study of systems that can learn from data, rather than follow only explicitly programmed instructions whereas Pattern recognition is the recognition of patterns and regularities in data [35]. Here in Jitterbug, the task of the pattern recognizer Easy is to find the strong patterns of the “easy to find” SATDs (RQ1). For each potential pattern (a keyword in the comments in our case), we measure two metrics:

- \( P(p) \): the number of comments containing the pattern \( p \) (positives).
- \( TP(p) \): the number of SATD comments containing the pattern \( p \) (true positives).

Derived from the above two metrics, we also have:

- \( Prec(p) = TP(p)/P(p) \): precision of the pattern \( p \).

For the reason of high reliability, we want to find those patterns with very high precision. On the other hand, we also want to avoid rare patterns, e.g. if a pattern only appears once, it is not useful even with 100% precision. As a result, we define our fitness function as:

\[
Fitness(p) = Prec(p)^N \cdot P(p) = TP(p)^N / P(p)^{N-1}
\] (1)

We set \( N = 4 \) to find patterns with close to 100% precision. Using our labeled training data, the pattern recognizer looks for the pattern with the highest fitness score, then removes comments containing that pattern from the training data and finds the next
patterns with the highest fitness score (re-calculated). The detailed algorithm is shown in Algorithm 2.

### 3.2 Hard

As shown in Algorithm 3, **Hard** utilizes a machine learner to continuously learn from both labeled data in the source projects and human decisions of comments in the target project. This machine learner in **Hard** can be any supervised learner in theory. However, since it will be updated/re-trained frequently, we only consider models that can be trained within seconds (users will not wait for more than a few seconds every time they finish a batch of comments). For this reason, we only test the following fast and simple learners listed below.

**Logistic Regression**: Logistic regression is a statistical model that in its basic form uses a logistic function to model a binary dependent variable [36]. A standard logistic function is a common "S" shape with Equation (2):

$$p(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}$$

where \(p(x) \in (0, 1)\) for all \(t\). Through fitting on the training data, logistic regression looks for the best parameter \(\beta\) to classify input data \(x\) into two target classes \((0,1)\).

**Decision Tree**: Decision tree learning is a method commonly used in data mining which uses a decision tree (as a predictive model) to go from observations about an item (represented in the branches) to conclusions about the item’s target value (represented in the leaves). Algorithms for constructing decision trees usually work top-down, by choosing a variable at each step that best
splits the set of items [37]. Two metrics are commonly applied to determine the best split:

- **Gini impurity**: \( I_G(p) = \sum_{i=1}^{J} p_i(1 - p_i) \).
- **Entropy**: \( I_E(p) = \sum_{i=1}^{J} p_i \log_2 p_i \).

Where \( J \) is the number of classes and \( p_i \) is the fraction of items labeled with class \( i \) in the training dataset. The algorithm will find the best split after which the value of \( I_G(p) \) or \( I_E(p) \) decreases the most. In this paper, we use gini impurity.

**Random Forest:** Random forest classifier is an ensemble learning method that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes of the individual trees [38]. Each decision tree from the random forest model is independently trained on all the training data but with only a subset of the features. In this way, these decision trees are 100% accurate on training data and yet have different generalization errors. When used together for inference, these decision trees correct for each other’s generalization errors and thus avoid overfitting on the training data.

**Naive Bayes:** Naive Bayes classifiers are a family of simple “probabilistic classifiers” based on Bayes’ theorem with strong (naive) independence assumptions between the features [39]. With the strong assumption that all features are mutually independent, a Naive Bayes classifier predicts the conditional probability of data \( x \) belonging to class \( C_t \) to be:

\[
p(C_k \mid x_1, \ldots, x_n) \propto p(C_k) \prod_{i=1}^{n} p(x_i \mid C_k) \tag{3}
\]

where \( p(C_k) \) and \( p(x_i \mid C_k) \) are counted from the training data. Multinomial Naive Bayes model assumes that each \( p(x_i \mid C_k) \) is a multinomial distribution, which works well for text data.

**Support Vector Machine:** A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane [40]. Soft-margin linear SVMs are commonly used in text classification given the high dimensionality of the feature space. A soft-margin linear SVM looks for the decision hyperplane that maximizes the margin between training data of two classes while minimizing the training error (hinge loss):

\[
\min \lambda \|w\|^2 + \left[ \frac{1}{n} \sum_{i=1}^{n} \max \{0, 1 - y_i(w \cdot x_i - b)\} \right] \tag{4}
\]

where the class of \( x \) is predicted as \( \text{sgn}(w \cdot x - b) \).

**Hard** also utilizes an estimator to estimate the number of “hard to find” SATDs and thus determine when to stop. This estimator, also described in Algorithm [3] is adopted from our previous work [32] where it was shown to outperform any other state-of-the-art estimators. The idea behind this estimator is that it (1) assigns temporary labels to unlabeled data points following the probability prediction from a logistic regression model, (2) then updates that logistic regression model on the temporary labeled data, (3) iterates the above two steps until convergence (when the number of temporarily assigned labels stays unchanged).

4 Datasets

While [3] shows how Jitterbug should be applied in practice with human reading source code comments looking for the “hard to find” SATDs, it is too expensive for humans to test different treatments and answer all the research questions. As a result, the performance of Jitterbug is tested through simulations on a publicly available SATD dataset originally collected by Maldonado and Shihab [23]. This dataset contains ten open-source java projects on different application domains (five of these projects were added by the same authors later after its first release), varying in size and the number of developers and most importantly, in the number of comments in source code. All of these ten projects, namely Apache-Ant-1.7.0, Apache-Jmeter-2.10, ArgoUML, Columba-1.4-src, EMF-2.4.1, Hibernate-Distribution-3.3.2.GA, jEdit-4.2, jFreeChart-1.0.19, jRuby-1.4.0, SQL12 were collected from GitHub. The provided dataset contains project names, classification type (if any) with actual comments. Note that, our problem does not concern with the type of SATD, rather we care about a binary problem of being a SATD or not. So, we have changed the final label into a binary problem by defining WITHOUT_CLASSIFICATION as no and the rest (for example DESIGN) as yes. A few examples from the dataset is given in Table 2 for readers ease.

| project          | classification | commenttext                                                                 | label  |
|------------------|----------------|-----------------------------------------------------------------------------|--------|
| apache-ant-1.7.0 | DEFECT         | // FIXME: formatters are not thread-safe                                     | yes    |
| emt-2.4.1        | IMPLEMENTATION | // TODO Binary incompatibility; an old override must override putAll.       | yes    |
| jfreechart-1.0.19| DESIGN         | // calculate the adjusted data area taking into account the 3D effect... // this assumes that there is a 3D renderer, all this 3D effect is a // bit of an ugly hack... | yes    |
| jruby-1.4.0      | WITHOUT CLASSIFICATION | // build first node (and ignore its result) and then second node         | no     |
| columba-1.4-src  | WITHOUT CLASSIFICATION | // get message header                                                         | no     |
| apache-jmeter-2.10| WITHOUT CLASSIFICATION | // parameters to pass to script file (or script)                     | no     |

**TABLE 2: Examples from Dataset**

4.1 Independent Variables

When creating this dataset, jDeodrant [42] was applied, which is an Eclipse plugin for extracting comments from the source code of java files. After that, they have used four filtering heuristics to the comments. A short description of them is given below.

- Removed licensed comments, auto generated comments etc because according to the dataset authors, they do not contain SATD by developers.
- Removed commented source codes as commented source codes do not contain any SATD.
- Removed Javadoc comments that do not contain the words such as "todo", "fixme", "xxx" etc. because according to the dataset authors, the rest of the comments rarely contain any SATDs.
- Multiple single line comments are grouped into a single comment because they all convey a single message and it is easy to consider them as a group.

After applying these heuristics, the number of comments in each project reduced significantly (for example, the number of comments in Apache Ant reduced from 21,587 to 4140, almost 97% of the original size).
4.2 Dependent Variables

Two humans then manually classified each comment according to the six different types of TD mentioned by Alves et al. [43] if they contained any SATD at all, else marked them WITHOUT CLASSIFICATION. Stratified sampling of the dataset was applied to check personal bias and found 99% confidence level with a confidence interval of 5%. A third human verified the agreement between the two using stratified sampling and reported a high level of agreement using Cohen’s Kapp coefficient of +0.81. Such a high confidence level as well as higher level of agreement indicates that the dataset is unbiased and reliable. A detailed description of the dataset is given in Table 3.

5 EXPERIMENTS AND RESULTS

Experiments are conducted on the SATD dataset with 10 projects described in Table 4. Each time, one project is selected as a target project (with labels unknown) and the rest 9 datasets are treated as source projects (with labels known). In Step 2, when oracles are queried for the target project, the ground truth labels are applied to label the queried comments, thus simulating the human-in-the-loop process without a real human in the loop. The rest of this section will provide details on the experiments and results for answering the research questions listed in Table 2.

5.1 RQ1: How to find the strong patterns of the “easy to find” SATDs in Step 1?

In this experiment, we compare the performance of the following two treatments

- **Easy**: The pattern recognizer of Jitterbug described in Algorithm 2 which iteratively selects the pattern with highest fitness score in Table 4 until the selected pattern has lower than 80% precision on the training data.
- **MAT**: a baseline approach from Guo et al. [3] where a set of human-derived patterns—“todo, fixme, hack, xxx” is applied to find the “easy to find” SATDs.

on three different performance metrics

- **Precision**: \( \text{Precision} = \frac{TP}{TP+FP} \).
- **Recall**: \( \text{Recall} = \frac{TP}{TP+FN} \).
- **F1 score**: \( F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \).

where \( TP \) is the number of true positives (SATD comments predicted as SATDs), \( FP \) is the number of false positives (non-SATD comments predicted as SATDs), and \( FN \) is the number of false negatives (SATD comments predicted as non-SATDs).

Table 3 (Original) shows the results of the experiment on the original dataset. Our observation from the results are:

1) Choosing any project as the holdout set, the strong patterns discovered by the pattern recognizer are always the same—“todo, fixme, hack, workaround”, except for jruby-1.4.0 where the strong patterns are “fixme, hack”.

2) Compared with manually discovered patterns—“todo, fixme, hack, xxx” from Guo et al. [3] (MAT), the patterns automatically learned by Easy showed higher or similar precision and recall on 8 out of 10 target projects.

The results above suggest that our automated pattern recognizer Easy performed better than the human-derived patterns from Guo et al. [3] (MAT). However, it did not reach close to 100% precision on many target projects as we expected. One possible reason for this is human errors—labels in the original dataset may not always be correct. Therefore we manually analyzed the false positives (comments containing the strong patterns but were previously wrongly labeled in the original dataset).

![Fig. 2: Validation results for double-checking false positives of Easy. The values of “yes (Easy)” show the number of comments that the double-checking result agrees with the Easy results (Easy=yes AND GT=no AND DC=yes) while the values of “no (GT)” show the number of comments that the double-checking result agrees with the original ground truth labels (Easy=yes AND GT=no AND DC=no). This graph shows that most (426 out of 434) of the false positives are actually true positives that were previously wrongly labeled in the original dataset.](image-url)
3) **Easy** is even more accurate than human experts in identifying the “easy to find” SATDs since 98% of the conflicting comments, which were labeled as Non-SATDs by human but contain the patterns from **Easy**, are identified as SATDs in our validation study.

4) Although **Easy** is an algorithm with close to 100% precision and barely any cost (training takes seconds), it alone can only identify 20% to 90% of the SATDs. Thus it is necessary for Step 2.

### 5.2 RQ2: How to better find the “hard to find” SATDs with less human effort in Step 2?

After all the “easy to find” SATDs are filtered out from the datasets, it is now a problem to find the rest “hard to find” SATDs (which are 10-80% of all the SATDs). To solve this problem, we first ask the following question.

#### 5.2.1 RQ2.1: Can the “hard to find” SATDs be automatically detected without human oracles?

To answer this question, we trained supervised learning models on source projects and tested them on the target project (both source projects and target projects do not contain comments that have the patterns identified by Step 1). The following models are evaluated in this experiment:

- **LR**: logistic regression model described in §3.2. Implemented with scikit-learn package LogisticRegression in Python with balanced class weight.
- **DT**: decision tree model described in §3.2. Implemented with scikit-learn package DecisionTreeClassifier in Python with balanced class weight.
- **RF**: random forest model described in §3.2. Implemented with scikit-learn package RandomForestClassifier in Python with class_weight = balanced_subsample.
- **SVM**: linear soft-margin support vector machine model described in §3.2. Implemented with scikit-learn package SGDClassifier in Python with balanced class weight.
- **NB**: Multinomial Naive Bayes model described in §3.2. Implemented with scikit-learn package MultinomialNB in Python.
- **TM**: ensemble model from Huang et al. [1] where a Multinomial Naive Bayes model is trained on selected features with information gain on each source project and the majority vote of the predictions from each model on the target project is utilized to make the final prediction. **TM** is considered as the state-of-the-art solution for identifying SATDs so here we apply it as a baseline algorithm.

To assess whether the above supervised learning models can identify the “hard to find” SATDs precisely without human oracles, the following metric is collected:

- **P@10**: precision for the top 10 predictions. For example, if there are 6 SATDs amongst the 10 comments with the highest prediction probability, $P@10 = 0.6$.

Figure 3 shows that at most three out of ten projects have **P@10** higher than 0.5. Therefore we conclude that directly using the model predictions as classification results will result in a large number of false positives. As a result, human experts have to verify each prediction result to decide whether it is SATD or not. This leads to our next research question.
TABLE 5: APFD (higher the better) results for different models with or without the Hard strategy on the “hard to find” SATDs. Medians and iqr s (lower the better) are calculated for easy comparisons. If Hard = no, human oracles on the target project are not utilized, the model is just a one-time trained supervised learning model. On the other hand, if Hard = yes, human oracles on the queried comments are utilized to update the model before it is applied to find its next highest predictions for humans to verify. Jitterbug utilizes Hard = yes. A threshold of Cohen’d small effect size (0.02) is applied to determine which treatment performs best in each target project and color them in gray. The column #Best shows the number of projects each treatment performs the best in.

| Model | Hard | sq12 | apachemeter-2.10 | emf-2.4.1 | apache-ant-1.7.0 | argouml | hibernate-distribution-3.2.2-GA | jEdit-4.2 | jFreechart-1.0.19 | columba-1.4-src | jruby-1.4.0 | Median | IQR | #Best |
|-------|------|------|------------------|-----------|------------------|--------|-----------------------------|----------|-----------------|---------------|-------------|---------|-----|-------|
| LR    | no   | 0.69 | 0.85             | 0.80      | 0.88             | 0.93   | 0.80                        | 0.80     | 0.80            | 0.80          | 0.83        | 0.82    | 0.07 | 2     |
| DT    | no   | 0.74 | 0.84             | 0.83      | 0.89             | 0.93   | 0.81                        | 0.85     | 0.81            | 0.92          | 0.83        | 0.84    | 0.07 | 3     |
| RF    | no   | 0.78 | 0.78             | 0.84      | 0.78             | 0.88   | 0.76                        | 0.86     | 0.71            | 0.87          | 0.86        | 0.81    | 0.08 | 0     |
| SVM   | no   | 0.71 | 0.64             | 0.71      | 0.77             | 0.8    | 0.77                        | 0.75     | 0.53            | 0.78          | 0.81        | 0.76    | 0.07 | 0     |
| NB    | no   | 0.81 | 0.78             | 0.83      | 0.83             | 0.88   | 0.78                        | 0.82     | 0.73            | 0.91          | 0.83        | 0.82    | 0.03 | 0     |
| TM    | no   | 0.91 | 0.83             | 0.75      | 0.83             | 0.90   | 0.75                        | 0.95     | 0.79            | 0.97          | 0.92        | 0.91    | 0.04 | 9     |
|       | yes  | 0.58 | 0.81             | 0.83      | 0.90             | 0.92   | 0.83                        | 0.93     | 0.79            | 0.97          | 0.92        | 0.91    | 0.05 | 8     |

5.2.2 RQ2.2: How to more efficiently utilize human oracles to find the “hard to find” SATDs?

Since it is inevitable to spend human effort on verifying the prediction results in Step 2, the Hard strategy is applied to learn from this incrementally acquired information and update its model for better predictions, as described in Algorithm 5. In this experiment, we record the recall and its corresponding cost (of human effort) for each algorithm as the cost increases:

\[
Recall = \frac{|\text{SATDs} \cap \text{human verified comments}|}{|\text{SATDs}|} \quad (5)
\]

\[
Cost = \frac{|\text{human verified comments}|}{|\text{all comments}|} \quad (6)
\]

To simplify the comparison between different algorithms, we calculate the area under the recall-cost curve as a performance metric:

- **APFD**: first proposed in test case prioritization [45]. APFD calculates the area under the recall-cost curve. Ranging from 0.0 to 1.0, a larger APFD means higher recall can be achieved with a lower cost, thus the better. An APFD of 0.5 can be achieved by randomly select the next item each time.

Table 5 shows the APFD results for different models with or without the Hard strategy. Given that most of the results are deterministic and are close to each other, we applied Cohen’d effect size test to determine which results are similar. To that end, we estimated the number of SATDs

\[
Estimation = \frac{\text{estimated number of SATDs}}{|\text{SATDs}|} \quad (8)
\]

Fig. 4: Recall-cost curves for three different treatments on finding the “hard to find” SATDs on target project sq12. Hard represents RF with Hard=yes while RF represents RF with Hard=no. APFD results in Table 5 were calculated as the area under these curves. Figures on other target projects are shown in the Appendix as Figure A.1.

- Random forest model with the Hard strategy outperformed the baseline algorithm TM on finding the “hard to find” SATDs. For a more intuitive comparison, Figure 4 shows the recall-cost curves of three different treatments on target project sq12. The APFD results in Table 5 were calculated as the area under these curves. As we can see, Hard (RF with Hard=yes) has the highest APFD score of 0.91. Also, in Figure 4 it almost always reaches the same recall with a lower cost than RF (RF with Hard=no) with APFD score of 0.82 and TM with APFD score of 0.73. Recall-cost curves on other target projects can be found in Figure A.1 from the Appendix.

5.2.3 RQ2.3: When to stop Hard in Step 2?

With an accurate estimation of the number of undiscovered SATDs, human experts are easier to make decisions on whether to spend more time looking for the “hard to find” SATDs or to stop at that point. To assess the accuracy of the estimation, we plot out the recall-cost curves with the following estimation:

\[
Estimation = \frac{\text{estimated number of SATDs}}{|\text{SATDs}|} \quad (8)
\]
the following issues in mind: Any conclusions made from this work must be considered with there are several validity threats [46] to the design of this study.

5.4 Threats to Validity

As we can see from Figure 5, Hard tends to overestimate in the beginning but converges to the actual value after around 10% cost and it does help to determine when has 90% recall been reached. These recall-cost and estimation-cost curves on other target projects can be found in Figure A.2 from the Appendix. Table 6 shows the final recall and cost when Hard stops at 90% recall through estimations. Overall, Hard could stop close to the target 90% recall with the estimations.

5.3 RQ3: Overall how does Jitterbug perform?

Table 7 shows the overall APFD scores for finding all the SATDs in the target project. Similarly to RQ2.2, we applied the following threshold from Cohen’s small effect size to determine the best treatments in each target project:

\[
Small_{\text{overall}} = 0.2 \cdot \text{StdDev} \text{(All APFD results)} = 0.01. \quad (9)
\]

From these results, we observed:

- Jitterbug outperforms the state of the art solutions like TM, RF and MAT+RF.
- Jitterbug (Easy+Hard) outperforms Easy+RF, which means the Hard strategy outperforms RF in Step 2 and this contributes to the overall performance.
- Jitterbug (Easy+Hard) outperforms Hard, which means applying Easy in Step 1 does contribute to the overall performance.

For a more intuitive comparison, Figure 6 shows the recall-cost curves of the compared treatments on target project sql12. The APFD results in Table 7 were calculated as the area under these curves. As we can see, Jitterbug has the highest APFD score of 0.97. Also, in Figure 6 it almost always reaches the same recall with a lower cost than other treatments. Recall-cost curves on other target projects can be found in Figure A.3 from the Appendix.

In conclusion, Jitterbug outperforms the state of the art solutions in identifying SATDs and both of the two components Easy and Hard contribute to the good performance.

Conclusion validity consists of the significance of the treatments. To enhance conclusion validity, we ran experiments on 10 different target projects and found that our proposed method always performed better than the state of the art approaches.

Internal validity focuses on how sure we can be that the treatment caused the outcome. To enhance internal validity, we heavily constrained our experiments to the same dataset, with the same settings, except for the treatments being compared.

Construct validity focuses on the relation between the theory behind the experiment and the observation. To enhance construct validity, we compared solutions with and without our strategies in Table 7 and showed that both components (Easy and Hard) improve the overall performance. However, we only showed that with our setting of featurization and default parameters of each learner, random forest learner is the best choice. What we have not shown is that whether the performance can get even better by tuning the parameters or using a different setting of featurization. We plan to explore that in our future work.

External validity concerns how widely our conclusions can be applied. In order to test the generalizability of our approach, we always kept a project as the holdout test set and never used any information from it in training. However, all the experiments we have done are simulations on the dataset. How will Jitterbug perform with a real human screening the comments remains to be a question for our future work.

6 Conclusion and Future work

Identifying self-admitted technical debts (SATDs) from source code comments is important to keep track of and manage them, thus maintaining a healthy software project. Current solutions cannot automate this process due to the lack of precision in machine learning models in predicting the SATDs. To reduce the human effort required in identifying SATDs, this paper first showed that there are two types of SATDs—(1) the “easy to find” SATDs that can be automatically identified with close to 100% precision; and (2) the “hard to find” SATDs that only human experts can make the final decisions on. Then a half-automated two-step approach was proposed to first apply a novel pattern recognition technique to learn strong patterns of the “easy to find” SATDs and utilize these patterns to identify the “easy to find” SATDs automatically; then (a) train/update a continuous learning model incrementally on both historical labeled data and
new human decisions, and (b) guide the human experts to screen the comments that most likely contain the “hard to find” SATDs according to the model’s prediction, iterate (a) and (b) until a target recall has been reached according to the model’s estimation. Based on simulation results on ten software projects, we conclude that

- **Step 1** solution Easy can find 20-90% of the SATDs with close to 100% precision automatically.
- **Step 2** solution Hard outperforms other step of the art methods in finding the rest “hard to find” SATDs (Hard finds more SATDs with less human effort).
- **Step 2** solution Hard can also provide an accurate estimation of the number of “hard to find” SATDs undiscovered, thus offers a practical way to stop at the target recall.
- Overall, the proposed two-step solution Jitterbug is most efficient in identifying SATDs.

That said, Jitterbug still suffers from the validity threats discussed in Section 5.4. To further reduce those threats and to move forward with this research, we propose the following future work:

1. Apply hyper-parameter tuning on data preprocessing and model configuration to see if our current conclusions still hold and whether tuning can further improve the performance.
2. Prototype Jitterbug as a tool and apply it with real human experts in the loop to collect usability feedback.
3. Explore more complex patterns (other than just single word patterns) as has been explored in Step 1.
4. Explore more advanced machine learning algorithms in Step 2 for finding the “hard to find” SATDs.
5. Extend the work to other types of technical debts. One important message this paper tries to convey is that—do not waste effort on finding the “easy to find” SATDs, future research on identifying SATDs should mostly focus on the “hard to find” SATDs.

### APPENDIX A

This appendix shows the recall-cost curves on every target project in Figure A.1, Figure A.2, and Figure A.3.

3. We ask for the reviewers’ opinion on where should these large figures be placed, in appendix, in a github repo, or in the body content?

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Fig. A.1: Recall-cost curves for finding “hard to find” SATDs on every target project.
Fig. A.2: Recall-cost and estimation-cost curves for finding 90% of the “hard to find” SATDs with \textbf{Hard} on every target project.
Fig. A.3: Recall-cost curves for finding all SATDs on every target project.