

Using Source Code Comments to Detect Self-admitted Design Technical Debt

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Abstract—During the development and maintenance of a software system, developers face unpredictable difficulties or pressures, and in many cases are forced to apply unconventional solutions to overcome these difficulties. For example, they might adopt insufficiently tested or temporary solutions (i.e., workarounds and hacks), neglect good design practices, and introduce inaccurate or incomplete documentation due to time constraints and pressure to meet deadlines. This phenomenon has been explained through the metaphor of Technical Debt.

Prior work has shown that one of the most impacting types of technical debt is design debt and that code comments embedded in the code can be used to detect *self-admitted* technical debt. Therefore, in this paper our main goal is to study Self-admitted Design Technical Debt. More specifically, we derive comment patterns that can be used to detect Self-admitted Design Technical Debt. Then, we perform a case study to determine the effectiveness of our approach at detecting Self-admitted Design Technical Debt. We also compare the effectiveness of our approach to prior approaches that use code smells to detect design technical debt and quantify how much of the self-admitted design debt can be automatically refactored with refactoring tools. We suggest 176 different comment patterns that can be used to detect Self-admitted Design Technical Debt. Our approach can achieve precision and recall values between 74.07-96.30% and 10.87-83.87%, respectively. We also show that our approach detects design technical debt that is different from alternative state-of-the-art techniques used for finding design technical debt. Lastly, our findings also show that 24.58% of the Self-admitted Design Technical Debt is detected in the form of refactoring opportunities by a state-of-the-art refactoring recommendation tool.

I. INTRODUCTION

Developers often have to deal with conflicting goals that require software to be delivered quickly, with high quality, and on budget. In practice, achieving all of these goals at the same time can be challenging, causing a tradeoff to be made. Often, these tradeoffs lead developers to take *shortcuts* or use *workarounds*. Although such shortcuts help developers in meeting their short-term goals, they may have a negative impact in the long-term.

Technical debt is a metaphor that has been used to express sub-optimal solutions that are taken consciously in a software project in order to achieve some short-term goals. Generally, these decisions allow the project to move faster in the short-term, but introduce an increased cost (i.e., debt) to maintain this software in the long run [1], [2]. Prior work showed that technical debt is widespread in the software domain, is unavoidable, and can have a negative impact on the quality of the software [3].

Due to the importance of technical debt, a number of studies empirically examined it and proposed techniques to enable its detection and management. The main findings of the prior work is that 1) there are different types of technical debt, e.g., defect debt, design debt, testing debt, and that design debt has the highest impact [4], [5]; and 2) statically analyzing the source code can help detecting technical debt [6]–[8]. In particular, these works use metric thresholds to detect code smells, which are considered as proxies for technical debt.

One major drawback of using metrics to detect technical debt is that no one knows if the detected smells really constitute technical debt, or if they correspond to problems that the developers care about. Therefore, more recently, our work showed that using code comments can be effective in identifying self-admitted technical debt [9]. This work uses comments to detect *generic* technical debt, and did not focus on any specific type of technical debt.

In this paper, we build on the promising approach of using code comments to detect one of the most impacting types of debt, namely *design technical debt*, which we call Self-admitted Design Technical Debt. We manually examine more than 17,000 code comments to extract comment patterns that can be used to detect Self-admitted Design Technical Debt. To examine the effectiveness of our approach, we perform an empirical study on ten open source projects. Finally, we compare our approach to state-of-the-art approaches and examine the effectiveness of using automated refactoring techniques in mitigating Self-admitted Design Technical Debt.

Based on our manual examination of the code comments, we derive 176 different comment patterns that can be used to detect Self-admitted Design Technical Debt. These patterns are able to detect Self-admitted Design Technical Debt with a precision ranging in 74.0-96.30% and a recall ranging in 10.87-83.87%. Moreover, we find that the design technical debt found with our approach is different than the design technical debt found using metric-based approaches [8]. Finally, we find that automated refactoring can address up to 24.58% of the methods containing Self-admitted Design Technical Debt.

The rest of the paper is organized as follows: Section II presents a motivating example. Section III details our approach. We present our case study results in Section IV, followed by a discussion in Section V. Section VI presents the related work. The threats to validity of our work are discussed in Section VII. Section VIII lists the conclusions of our work.

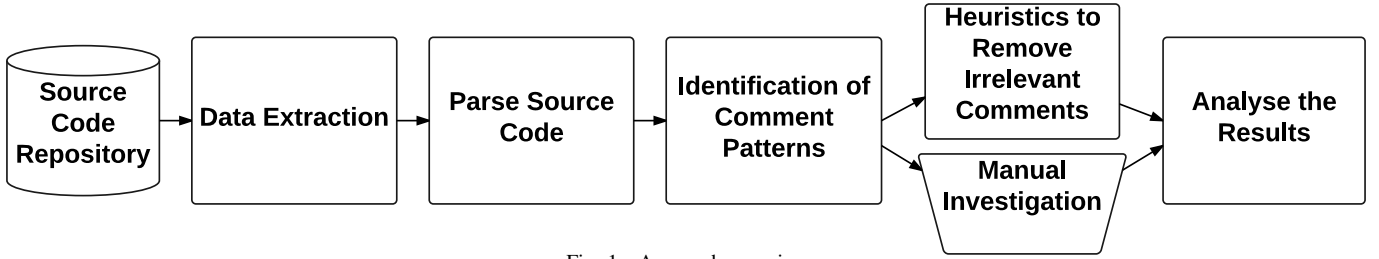


Fig. 1. Approach overview

II. MOTIVATING EXAMPLE

As mentioned earlier, one of the first works on self-admitted technical debt was the work by Potdar and Shihab [9]. Their work showed that it is possible to identify self-admitted technical debt using source code comments. However, in their work, Potdar and Shihab studied *generic* technical debt, i.e., they did not discriminate between the different types of technical debt. For example, technical debt can be in the form of design debt, testing debt, defect debt, and documentation debt.

Since our work focuses on Self-admitted Design Technical Debt, we first examined the effectiveness of using the general comments used by Potdar and Shihab to detect design technical debt. We applied the comment patterns that we derived (which we present later in the paper) and the comment patterns from Potdar and Shihab on the studied open source projects. As expected, the results produced by the general comment patterns identified all types of technical debt, indicating the need for more specific comment patterns that can be used to effectively identify design technical debt.

To illustrate our point, we show some example comments flagged by Potdar and Shihab's approach in the first column of Table I. The second column of the table shows the comments that are detected by the comment patterns we propose in this paper, which focus on Self-admitted Design Technical Debt. A comparison of the comments in Table I clearly shows that the more specific comment patterns detect design issues.

This simple example shows that comment patterns that specifically target design technical debt are needed. Simply using the general comment patterns may yield unfavourable results. We elaborate more on the performance of using the general comment patterns to detect Self-admitted Design Technical Debt in Section IV.

III. APPROACH

The main goal of our study is to extract comment patterns that can be used to effectively identify Self-admitted Design Technical Debt. Figure I shows an overview of our approach. The following subsections detail each step of our approach.

A. Data Extraction

To perform our study, we obtain the source of ten large open source projects, namely Apache Ant, Jakarta Jmeter, ArgoUML, Columba, EMF, Hibernate, JEdit, JFreeChart, JRuby and Squirrel SQL Client. We chose the aforementioned

projects, since they belong to different domains, and vary in size (e.g., LOC), and in the number of contributors.

Table II provides statistics about each of the projects used in our study. In total, we obtained more than 258,878 comments, found in 16,249 files. We also include the release used, the number of classes, and the total lines of code (LOC). In our study, we only use the Java files to calculate the LOC. It is important to notice that the number of comments shown for each project does not represent the number of commented lines, but rather the number of individual line, block, and Javadoc comments.

B. Parse Source Code

After obtaining the source code of all projects, we extract the comments from their source code. We use JDeodorant [10], an open-source Eclipse plug-in, to parse the source code and extract the code comments. Once extracted, we store all comments in a relational database to facilitate the processing of the data.

C. Identification of Self-admitted Design Technical Debt Comment Patterns

Once we store all comments in the database, our next step is to identify the Self-admitted Design Technical Debt comment patterns. Since we are dealing with natural language in the comments, it is challenging to automatically determine what comments indicate design technical debt. Therefore, we opted to use two different approaches to determine comment patterns that indicate design technical debt. First, we use the terms mentioned in prior work [11]–[13] (i.e., code smell and anti-pattern names) as indicators of design problems to determine comments that are indicative of design technical debt. Second, we manually examined and classified all comments of one project i.e., Apache Ant, in order to determine comment patterns that are indicative of Self-admitted Design Technical Debt. After analyzing the results, we found that combining comment patterns from the two aforementioned approaches provides the best results. We detail the steps taken to achieve each of the two approaches.

1) *Applying Heuristics to Eliminate Irrelevant Comments:* When applying our first approach, i.e., using the terms in the prior work to identify comments that are indicative of Self-admitted Design Technical Debt, we found that we are able to flag comments that indicate design issues, but also flag many false positives. We analyzed the false positives to see whether

TABLE I
EXAMPLE OF GENERAL/DESIGN SELF-ADMITTED TECHNICAL DEBT COMMENTS

General Self-Admitted Technical Debt	Self-Admitted Design Technical Debt
<i>remove this code once bug 62405 is fixed for the mainstream GTK</i> <i>FIXME - This caching thing should not be here; it's brittle.</i> <i>FIXME compat: updateActionBars : should do something useful</i> <i>FIXME this does not actually set the default since it is the wrong</i> <i>TODO: - please add some javadoc - ugly classname also</i>	<i>This can lead to code smell, meh! Do we care</i> <i>This is an absurdly long method! Break it up.</i> <i>there should be an interface, instead of the AbstractMessageFolder</i> <i>rethink where exactly some of the following methods belong (Gen-Model or GenPackage)</i> <i>Cyclic dependency with PersistenceManager</i>

TABLE II
CASE STUDY PROJECT DETAILS AND STATISTICS

Project	Release	LOC	Classes	Comments	Contributors	Description
Apache Ant	1.7.0	115,881	1,475	21,587	70	A Java library and command-line tool to build Java applications.
Jakarta Jmeter	2.3.2	81,307	1,181	20,084	32	An application to measure performance and assert functional behavior.
ArgoUML	0.34	176,839	2,609	67,716	87	An UML modeling tool.
Columba	1.4	100,200	1,711	33,895	9	A desktop email client written in Java.
EMF	2.4.1	228,191	1,458	25,229	28	Eclipse Modeling Framework.
Hibernate	3.3.2 GA	173,467	1,356	11,630	216	An Object Relational Mapping framework.
JEdit	4.2	88,583	800	1,6991	55	A light weight text editor.
JFreeChart	1.0.19	132,296	1,065	23,123	18	A Java library to display graphics and charts.
JRuby	1.4.0	150,060	1,486	11,149	291	Is the implementation of the Ruby language using the Java Virtual Machine.
Squirrel	3.0.3	215,234	3,108	27,474	40	A graphical SQL client written in Java.

we can gain any insight into why they appear and how we can eliminate them.

We identified three main types of false positives. First, license comments, containing copyright information and legal rights. Second, commented source code containing Java keywords, e.g., “big” and “long”. Finally, Javadoc comments were flagged, however, they often had no relation to design issues. As a result, we came up with three heuristics and a post-processing step to reduce the number of false positives.

- **Heuristic to remove license comments.** When license comments are added to the Java files in a project they are generally placed in the first lines of the file, before the class declaration. Based on this knowledge we created a heuristic that eliminates comments that are placed before the class declaration. To validate the result of this heuristic we examined a sample of the comments being removed to check if they were indeed license comments. We noticed that some comments were placed before the class declaration although they were not license comments. To mitigate the risk of eliminating important comments, we added one more condition: If the comment contains one of the task-reserved words (e.g. “todo”, “fixme”, or “xxx”) we do not remove the comment.
- **Heuristic to remove commented source code.** If a commented piece of source code contains Java keywords like “long” or “big”, it will increase the number of false positives of our approach. Commented source code can be found for several different reasons. One of the possibilities could be that the code is not being currently used, or if the particular piece of code is used to debug

the program. Since commented code does not have Self-admitted Design Technical Debt, we remove commented source code using a regular expressions that captures typical Java code structures.

- **Heuristic to remove Javadoc comments.** The Javadoc comments contain information about the purpose and use of methods and classes. That said, Javadoc comments rarely mention Self-admitted Design Technical Debt. Therefore, we create a heuristic that removes Javadoc comments. To mitigate the risk of eliminating some correct cases, we added one exception - if the comment contains one of the task-reserved words (e.g. “todo”, “fixme”, or “xxx”) we keep that Javadoc comment.
- **Post processing technique to merge multiple line comments** Another problem that we found while analyzing the comments was that some times developers make long comments, using multiple single-line comments instead of a Block comment. Treating every single line of a long comment as an individual comment causes us to miss important context details that could be recovered by treating all single-line comments as a single block comment. Therefore, we create a post processing technique that searches for consecutive single-line comments and groups them.

The steps mentioned above significantly reduced the number of comments in our dataset and helped us focus on the most applicable and insightful comments. For example, in the Apache Ant project, applying the above steps helped reduce the number of comments from 21,587 to 4,436 comments.

TABLE III
NUMBER OF COMMENTS AFTER THE APPLICATION OF EACH HEURISTIC

Project	Initial no. of Comments	After license heuristic	After comment code heuristic	After Javadoc heuristic	After post processing
Apache Ant	21,587	20,421	20,268	6,239	4,436
Jakarta Jmeter	20,084	18,840	18,530	12,360	8,126
ArgoUML	67,716	28,180	27,848	13,972	10,303
Columba	33,895	14,600	14,256	9,095	6,825
EMF	25,229	24,355	24,093	8,861	5,868
Hibernate	11,630	10,446	10,277	4,908	3,071
JEdit	16,991	16,128	16,037	13,118	11,232
JFreeChart	23,123	22,114	22,047	5,902	4,449
JRuby	11,149	10,274	10,080	6,887	5,176
Squirrel	27,474	25,566	25,196	13,713	8,627

2) *Manual investigation of identified Self-admitted Design Technical Debt comments:* In addition to using the words that indicate design issues to detect Self-admitted Design Technical Debt, we also manually examine our dataset to extract comment patterns that indicate Self-admitted Design Technical Debt comments. We started by examining all of the 4,436 comments for the Apache Ant project and classified each comment as being related to Self-admitted Design Technical Debt or not. Since our focus in this work is on design debt, comments related to other types of technical debt were not labeled as Self-admitted Design Technical Debt comments. The classification of the Apache Ant comments took approximately 32 hours and was performed by the first author of the paper.

Manual Examination of Comments to Identify Self-admitted Design Technical Debt Comment Patterns

In the end of the classification we identified 93 Self-admitted Design Technical Debt related comments out of 4,436 comments in Apache Ant project.

Our next goal was to abstract the comments and come up with a set of *comment patterns* that indicate Self-admitted Design Technical Debt. Comment patterns are general patterns that represent one or more comments. Simply using a single word to identify Self-admitted Design Technical Debt comments can be misleading since the context that the word appears in can completely change the meaning of that word. In order to address this issue, we take into consideration some of the other words that appear in the same sentence to combine them into what we call comment patterns.

By the end of this step, we had identified the comment patterns that indicate Self-admitted Design Technical Debt. **In total, we had 176 comment patterns that can be used to detect Self-admitted Design Technical Debt.** To facilitate future work in the area, we make our dataset and the comment patterns publicly available ¹.

Table IV provides a sample of the comment patterns that we used to identify Self-admitted Design Technical Debt comments. The ‘%’ symbol indicates that the pattern uses the SQL language wildcards. Wildcards make the query to match anything before or after the wildcard symbol. For example, “dependen%” would result in positive results for comments

TABLE IV
SAMPLE SELF-ADMITTED DESIGN TECHNICAL DEBT COMMENT PATTERNS

Related Comment Patterns
‘%future%may%’
‘%future%better%’
‘%future%enhance%’
‘%future%change%’
‘%dependency%cycle%’
‘%todo%dependenc%’
‘%fixme%dependenc%’
‘%xxx%dependenc%’

that contains the words “dependency” or “dependencies”.

Once we derive the 176 comment patterns that indicate Self-admitted Design Technical Debt, we use these patterns to answer our research questions, which we detail in the next section.

IV. CASE STUDY RESULTS

The goal of our study is develop an effective way to detect Self-admitted Design Technical Debt. To do so, we first derive comment patterns that can be used to detect Self-admitted Design Technical Debt (RQ1). Then, we examine the effectiveness of the derived comment patterns in detecting Self-admitted Design Technical Debt in real-life open source projects (RQ2). We detail the motivation, approach and present the results of each of our research questions in the remainder of this section.

RQ1. What comment patterns indicate self-admitted design technical debt? How are these comment patterns different than previously proposed comment patterns?

Motivation: Prior work has shown that comments, embedded in the source code, are a good indicator of technical debt [9]. However, the prior work did not discriminate between the different types of debt. Since we know that design technical debt is one of the most impactful types of technical debt [5], we would like to derive specific comment patterns that are indicative of design technical debt.

Approach: Our general approach to derive the Self-admitted Design Technical Debt comment patterns was detailed in Sec-

¹http://users.encs.concordia.ca/~e_silvam/publications.html

tion III. In a nutshell, we start by using common words that are indicative of design issues listed in prior work (e.g., [11]–[13]). Since using these words returns many irrelevant comments (e.g., licensing and Javadoc comments), we use a number of heuristics to reduce the number of comments so that the most relevant comments are returned. Finally, we perform a manual examination to derive the final list of 176 comment patterns that best indicate Self-admitted Design Technical Debt.

Once we have the comment patterns, we apply them on ten open source projects namely - Apache Ant, Jakarta Jmeter, ArgoUML, Columba, EMF, Hibernate, JEdit, JFreeChart, JRuby and Squirrel SQL Client - in order to determine what comments are flagged and how common the different comment patterns indicate Self-admitted Design Technical Debt.

Furthermore, we compare the similarity of the comments detected using the comment patterns we derive in this paper to the *generic* comment patterns proposed in prior work [9]. To do so, we manually read the comments of three projects (i.e., Apache Ant, Jmeter and JFreeChart²) and labeled each comment as a design technical debt related comment or not. Then, we used our comment patterns and the generic comment patterns from prior work to detect the labeled design technical debt comments. Finally, to see how different (or similar) the comment patterns are, we report the amount of overlap for each of the three projects.

Results: In total, we derived 176 different comment patterns that indicate Self-admitted Design Technical Debt. Table V shows the ten top most common comment patterns that indicate Self-admitted Design Technical Debt in all projects. The first column of Table V lists the comment pattern and the second column lists the frequency that the comment pattern matched one of the manually labeled design technical debt comments in the three studied projects. From the table, we observe that “hack” is the most common pattern, followed by “todo+remove” and so on. It is important to note here that Table V only lists the top ten most common patterns, we provide a full list of all the 176 comment patterns in ³.

When we examined the comment patterns derived in our paper and the general comment patterns from the prior work, we noticed a significant difference. However, we also noticed some similarities. For example, the comment pattern “hack” shows up in both, our design specific comment patterns and the generic comment patterns. Therefore, to compare how different (or similar) the two approaches are, we applied both approaches on the three projects with the manually labeled comments.

Table VI shows the number of comments that indicate design technical debt (second column), the number of comments flagged by our comment patterns (third column), the number of comments flagged by the generic comment patterns (fourth column), and the overlap between the comments flagged by both approaches. First, we find that our approach flags more Self-admitted Design Technical Debt comments, with the

TABLE V
THE TOP TEN MOST COMMON SELF-ADMITTED DESIGN TECHNICAL DEBT COMMENT PATTERNS ACROSS ALL TEN PROJECTS

Pattern	Number of occurrences	Percentage
'%hack%'	32	19.75%
'%not %sure %'	9	5.56%
'%should%instead%'	9	5.56%
'%todo%remove%'	8	4.94%
'%ugly%'	6	3.70%
'% fix for %'	6	3.70%
'%why%not%'	6	3.70%
'%todo%duplicat%'	5	3.09%
'%todo%public%'	5	3.09%
'%idea?%'	4	2.47%

exception of JFreeChart. Second, we notice that the overlap is small, but close to the number of comments flagged by the generic comment patterns. This means that in most cases, the comments flagged by the generic comment patterns will be covered by the comments flagged using our approach, since the overlap is close to the generic comment patterns value.

To perform this analysis we took in consideration all the matches that each of the patterns retrieve. It's possible that one or more patterns match the same comment.

We find that the top 5 most common comment patterns are: hack, not+sure, should+instead, todo+remove and ugly. The comment patterns proposed in our approach flag more Self-admitted Design Technical Debt compared to the generic comment patterns proposed in prior work.

RQ2. Can we effectively detect self-admitted design technical debt using the proposed comment patterns?

Motivation: After deriving the comment patterns to detect Self-admitted Design Technical Debt, one of the first questions that comes to mind is - how effective are the proposed comment patterns in detecting Self-admitted Design Technical Debt. Determining the effectiveness of the comment patterns will give us confidence in their ability to detect Self-admitted Design Technical Debt in software projects.

Approach: To measure the effectiveness of our proposed comment patterns in detecting Self-admitted Design Technical Debt, we use the common measure of precision and recall. Precision measures how many of the comments our patterns flag as being Self-admitted Design Technical Debt, actually are Self-admitted Design Technical Debt. To calculate precision, we apply the 176 comment patterns to all the comments in the ten projects and then manually determine which of the flagged comments are actually Self-admitted Design Technical Debt. Recall measures how many of the actual Self-admitted Design Technical Debt in each project, our comment patterns are able to detect. To calculate recall, we apply our comment patterns on the three projects that we manually classified each comment for. Then, we measure the percentage of all the

²Note: since this analysis required us to manually examine and label each comment, we only performed this analysis on three of the ten projects.

³http://users.encs.concordia.ca/~e_silvam/publications.html

TABLE VI
COMPARING THE USE OF DESIGN-SPECIFIC COMMENT PATTERNS AND THE GENERIC COMMENT PATTERNS IN DETECTING SELF-ADMITTED DESIGN TECHNICAL DEBT

Project	Total # of Design Comments	# of Comments Our Approach Flags	# of Comments Generic Approach Flags	Overlap
Apache Ant	93	78	16	13
Jakarta Jmeter	243	66	24	23
JFreeChart	92	10	13	5

comments that are actually Self-admitted Design Technical Debt comments (true occurrences) that were detected by our comment patterns. Since the calculation of recall requires that we read each comment manually, we only calculate the recall for three of the ten projects.

Results: Table VII shows the precision and recall values of our approach. As explained earlier, since recall required the manual examination of all code comments, we only present the recall of three of the ten projects. We observe that the precision values for all the projects is good, ranging between 74.07-96.30%. However, the recall values are not as high, ranging between 10.87-83.87%. It is important to note here that the highest precision and recall values are achieved for Apache Ant, which is the project we mainly used to derive the comment patterns.

The consistently high precision values show that our comment patterns have a low false positive rate, i.e., comments flagged using our comment patterns are most likely Self-admitted Design Technical Debt. However, the low recall values (on the projects other than Apache Ant) indicate that our comment patterns will not flag all the *actual* comments indicating Self-admitted Design Technical Debt. In a nutshell, our comment patterns tend to be more conservative, reducing wasted effort, however the price to pay is that we may miss some of the Self-admitted Design Technical Debt comments in the code.

To better understand the reason for the low recall values, we manually investigated some of the comments that indicate Self-admitted Design Technical Debt in Jmeter and JFreeChart and found that some projects use project specific comment conventions that our comment patterns miss to capture. For example, in JFreeChart most of the Self-admitted Design Technical Debt comments were preceded with a “FIXME:”. That said, the high recall value achieved for Apache Ant shows that high recall values are achievable, however, one needs to examine and take into account the specific comment conventions used in that specific project. In the future, we plan to use Natural Language Processing techniques in order to derive comment patterns that may be applied across projects to detect Self-admitted Design Technical Debt.

Our comment patterns can detect Self-admitted Design Technical Debt comments with a precision between 74.07-96.30% and a recall between 10.87-83.87%.

TABLE VII
PRECISION AND RECALL OF OUR APPROACH

Project	Precision	Recall
Apache Ant	96.30%	83.87%
Jakarta Jmeter	88.00%	27.16%
JFreeChart	83.33%	10.87%
ArgoUML	88.05%	-
Columba	74.07%	-
EMF	85.18%	-
Hibernate	87.18%	-
JEdit	81.92%	-
JRuby	88.07%	-
Squirrel	88.57%	-

V. DISCUSSION

Thus far, our study has focused on determining comment patterns that can be used to detect Self-admitted Design Technical Debt and examining the effectiveness of our comment patterns in detecting Self-admitted Design Technical Debt. However, how our approach compares to existing approaches is an interesting question that is left unanswered. Therefore, in this section, we compare our approach to existing state-of-the-art approaches that have been used to detect design technical debt [14]. Then, we discuss the applicability of using refactoring recommendation systems to address Self-admitted Design Technical Debt.

A. Comparing our Comment-based Approach to the State-of-the-art in Design Technical Debt Detection

Prior work by Zazworka *et al.* [14] was one of the first to focus on the detection of design technical debt. In their work, the authors use Marinescu’s [6] detection strategies to identify God classes. It is assumed that God classes are strong indicators of design technical debt. Our approach aims to solve the same problem, i.e., the detection of design technical debt, however, we use code comments to answer detect the design technical debt. Therefore, one question that arises is: *are we finding the same design technical debt or do the two approaches complement each other?*

To answer this question, we implemented Marinescu’s metrics in the JDeodorant tool to detect God classes in all of the analyzed projects. Then, we measure the overlap between the files that our approach flags as having Self-admitted Design Technical Debt and the files that contain God classes. A high overlap means that we are indeed finding the same design technical debt issues as the state-of-the-art work. A

low overlap means that our approach complements the state-of-the-art approach, i.e., each approach finds different types of design technical debt.

Design technical debt has been studied before from several perspectives but, until now, not from the developers' comments perspective. Therefore, we would like to compare how our proposed approach compares with proved techniques used in previous studies [14]. Zazworka used Marinescu's [6] detection strategies to identify god classes as they are a strong indicator to design technical debt. Thus, we used the same detection strategies to identify the god classes in each one of our projects and then we compare the overlap with design technical debt comments found on these files.

Table VIII shows that there is very little overlap between the design technical debt issues flagged by our approach and the prior approach using God classes. We observe that in the best case, which is for the Jmeter project, only 5 files overlap. Another important observation from Table VIII is that in all projects, except for JFreeChart, our approach flags more files as having design technical debt. Based on this finding, we suggest that both approaches, i.e., our approach and the approach based on God classes, should be used to maximize the detection of technical debt.

B. Using Refactoring Recommendation Systems to Mitigate Self-admitted Design Technical Debt

Thus far, all of our work has focused solely on the *detection* of design technical debt. One question that still lingers is *What can we do to mitigate this design technical debt?* Many approaches can be employed to mitigate design technical debt, however, in this subsection, we focus on the use of refactoring recommendation systems to mitigate Self-admitted Design Technical Debt.

In order to examine the applicability of using refactoring to mitigate Self-admitted Design Technical Debt, we use the refactoring recommendations provided by JDeodorant. In particular, we run JDeodorant on all the projects. JDeodorant analyzed the source code and suggested four types of refactoring opportunities: Extract Class, Type-check Elimination, Extract Method and Move Method. We passed in the class names identified using our approach as being Self-admitted Design Technical Debt and recorded whether JDeodorant would suggest a refactoring. Then, we check whether the refactoring opportunities suggested by JDeodorant are in the same method (using the method signatures) that we found the Self-admitted Design Technical Debt comment in.

We find that out of 964 Self-admitted Design Technical Debt, JDeodorant recommended refactoring opportunities for 237 methods that contain Self-admitted Design Technical Debt comments. The refactoring opportunities were distributed as follows: The tool identified fifteen Move Method opportunities. The Move Method refactoring can improve cohesion and reduce coupling by grouping methods that should be placed together. Ninety Extract Method opportunities were suggested. Extract Method refactoring improves code readability and increases the usability of the methods by breaking long methods

into smaller methods. On the other hand, 132 methods with Self-admitted Design Technical Debt were participating in an Extract Class refactoring opportunity. The Extract Class refactoring is applied when addressing the Single Responsibility Principle violations.

In total, 24.58% of the methods containing Self-admitted Design Technical Debt comments had at least one refactoring opportunity suggested by the tool during our analysis.

VI. RELATED WORK

Our work uses code comments to detect Self-admitted Design Technical Debt. Therefore, we divide the related work into three categories: source code comments, technical debt, and code smell detection.

A. Source Code Comments

A number of studies examined the co-evolution of source code comments and the rationale for changing code comments. For example, Fluri *et al.* [15] analyzed the co-evolution of source code and code comments, and found that 97% of the comment changes are consistent. Tan *et al.* [16] proposed a novel approach to identify inconsistencies between Javadoc comments and method signatures. Malik *et al.* [17] studied the likelihood of a comment to be updated and Found that call dependencies, control statements, the age of the function containing the comment, and the number of co-changed dependent functions are the most important factors to predict comment updates.

Other work used code comments to understand developer tasks. For example. Storey *et al.* [18] analyzed how task annotations (e.g., TODO, FIXME) play a role in improving team articulation and communication. The work closest to ours is the work by Potdar and Shihab [9], where code comments were used to identify technical debt.

Similar to some of the prior work, we also use source code comments to identify technical debt. However, our main focus is on the detection of Self-admitted Design Technical Debt. As we have shown, our approach yield different and better results in detection Self-admitted Design Technical Debt. Furthermore, we propose comment patterns, that are derived from source code comments, to detect Self-admitted Design Technical Debt.

B. Technical Debt

A number of studies have focused on the study of, detection and management of technical debt. Much of this work has been driven by the Managing Technical Debt Workshop effort. Fore example, Seaman *et al.* [1], Kruchten *et al.* [2] and Brown *et al.* [19] make several reflections about the term technical debt and how it has been used to communicate the issues that developers find in the code in a way that managers can understand. Other work focused on the detection of technical debt. Zazworka *et al.* [8] conducted an experiment to compare the efficiency of automated tools in comparison with human elicitation regarding the detection of technical debt. They found that there is small overlap between the two approaches,

TABLE VIII
GOD CLASSES VS. DESIGN TECHNICAL DEBT COMMENTS

Project	Total classes	God classes	Design TD Classes	Overlap
Apache Ant	1,475	11	63	1
Jakarta Jmeter	1,181	19	60	5
ArgoUML	2,609	25	193	3
Columba	1,711	18	23	1
EMF	1,458	25	21	0
Hibernate	1,356	13	78	0
JEdit	800	7	55	0
JFreeChart	1,065	9	9	0
JRuby	1,486	23	76	0
Squirrel	3,108	30	75	1

and thus it is better to combine them than replace one with the other. In addition, they concluded that automated tools are more efficient in finding defect debt, whereas developers can realize more abstract categories of technical debt. In follow on work, Zazworka *et al.* [14] conducted a study to measure the impact of technical debt on software quality. They focused on a particular kind of design debt, namely God Classes. They found that God Classes are more likely to change, and therefore, have a higher impact in software quality. Fontana *et al.* [20] investigated design technical debt appearing in the form of code smells. They used metrics to find three different code smells, namely God Classes, Data Classes and Duplicated Code. They proposed an approach to classify which one of the different code smells should be addressed first, based on a risk scale. Also related here, Potdar and Shihab [9] used code comments to detect technical debt. They extracted the comments of four projects and analyzed more than 101,762 comments to come up with 62 patterns that indicates self-admitted technical debt. Their findings show that 2.4% - 31% of the files in a project contain self-admitted technical debt.

Our work is different from the work that uses code smells to detect design technical debt since we use code comments to detect design technical debt. Also, our focus is on *self-admitted* design technical debt. As we have shown in the discussion section, there is very little overlap between the Self-admitted Design Technical Debt that our approach detects and the design technical debt detected using code smells (in particular God classes).

C. Code Smell Detection

Other work build tools and techniques to facilitate the detection of code smells. Moha *et al.* [21] proposed DECOR, a tool that incorporates a set of techniques to identify code smells in the source code. They used a domain specific language (DSL) to specify code smell detection rules. Their approach automatically generates detection algorithms based on the code smell specifications. They evaluated their techniques in 11 open-source projects and found that DECOR can effectively detect code smells, with an average precision of 60.5% and recall of 100%. Palomba *et al.* [22] proposed an approach to identify code smells based on the evolution of the source code. In order to do that they mined the history change from the

source code repository and then they searched for bad smells. They show that using their approach (HIST), they are able to identify 5 different bad smells. Tsantalis *et al.* [23] proposed a methodology that identified Feature Envy bad smells and evaluated the refactoring to remove the bad smell.

Our work complements the prior work on code smell detection, since we propose the use of code comments to detect Self-admitted Design Technical Debt. In particular, we propose 176 comment patterns to identify Self-admitted Design Technical Debt. Analyzing the source code comments using our approach in addition to the source code analysis techniques already employed in prior work can lead to optimal results, since our analysis showed that our approach yields results that are complementary to what code smell approaches detects.

VII. THREATS TO VALIDITY

Internal validity consider the relationship between theory and observation, in case the measured variables do not measure the actual factors. The comment patterns derived by us heavily relied on manual analysis of the code comments from Apache Ant. Like any human activity, our manual classification is subject to personal bias. To reduce this bias, any comment that was questionable was discussed between the three authors of the paper. When performing our study, we used well-commented Java projects. Since our technique heavily depends on code comments, our results and performance measures may be impacted by the quantity and quality of comments in a software project.

When we investigate if there are refactoring recommendations to address the detected Self-admitted Design Technical Debt, we essentially examine if the methods in which design debt is found participate in any of the refactoring opportunities suggested by JDeodorant. The presence of a refactoring opportunity for a given method, may not necessarily address the same kind of design debt described in the comment. In the future, we plan to investigate in a more fine-grained level the applicability of the suggested refactorings to Self-admitted Design Technical Debt.

When calculating the precision and recall values, we needed to manually examine the comments and label them as related to Self-admitted Design Technical Debt or not. Any errors

in our labeling may impact the precision and recall values reported.

External validity consider the generalization of our findings. All of our findings were derived from comments in open source projects. To minimize external validity, we chose open source projects from different domains. That said, our results may not generalize to other open source or commercial projects. In particular, our results may not generalize to projects that have a low number or no comments.

VIII. CONCLUSION AND FUTURE WORK

The term Technical Debt is often used to express some kind of inadequacy in the source code in a way that is understandable to management. But this metaphor can represent many different kind of things, inappropriate or temporary solution to meet a deadline, error prone code, lack of tests and documentation and even design flaws or workarounds. Sometime, developers are aware of these problems and they may express their concern through comments in the source code. Therefore, in this study we propose an approach to identify such comments in the source code. Our findings show that:

- The derived 176 comment patterns can be used to effectively identify Self-admitted Design Technical Debt, with precision values ranging between 74.07-96.30% and recall values ranging between 10.87-83.87%.
- The design technical debt identified by our approach is different than the design technical debt detected through code smells.
- Approximately 24.58% of the detected Self-admitted Design Technical Debt can be automatically refactored with automated refactoring tools.

We believe that our study lays the ground work for future work in the area of self-admitted technical debt. In the future, we plan to explore Natural Language Processing techniques in order to improve the detection of Self-admitted Design Technical Debt across projects. Furthermore we plan to expand the current taxonomy to include more categories of technical debt like defect and test technical debt. Finally, we plan to explore the use of our technique to possibly rank refactoring candidates suggestions from automated tools based on the type of technical debt.

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APPENDIX

Table IX lists all of the comment patterns derived in our study. If the paper is accepted, this appendix will be provided through an online link. We include this appendix, which

will be removed later, so that reviewers need not go to an online link during the review process. Online links have been discouraged in the past during the review process since they may indicate the identity of the anonymous reviewers.

TABLE IX
THE DERIVED 176 COMMENT PATTERNS THAT INDICATE SELF-ADMITTED DESIGN TECHNICAL DEBT

'%future%may%'	'%perhaps%elsewhere%'	'%hard%coding%'	'%todo%complex%'
'%future%better%'	'%rather%complex%'	'%kludge%'	'%fixme%complex%'
'%future%enhance%'	'%held%?%'	'%todo%public%'	'%xxx%complex%'
'%future%change%'	'%though%unused%'	'%fixme%public%'	'%consistency%sake%'
'%quick%fix%'	'%todo%don%know%'	'%xxx%public%'	'% lack %broke%'
'%temporary%until%'	'%fixme%don%know%'	'%messy%'	'% lack %problem%'
'%place%somewhere%else%'	'%xxx%don%know%'	'%should%instead%'	'% lack %should%'
'%move%somewhere%else%'	'%don%know%try%'	'%this%weird%'	'%todo% lack %'
'%used%other%place%'	'%don%know%fail%'	'%weird%this%'	'%fixme% lack %'
'%it %may %change %'	'%don%know%what%'	'%todo%weird%'	'%xxx% lack %'
'%this may change%'	'%don%know%fix%'	'%fixme%weird%'	'%todo% long %'
'%todo%can%change%'	'%not%fond%'	'%xxx%weird%'	'%fixme% long %'
'%fixme%can%change%'	'%more%elegant%'	'%todo%availability%'	'%xxx% long %'
'%xxx%can%change%'	'%clean%way%'	'%fixme%availability%'	'%todo% large %'
'%not %sure %'	'%todo%remove%'	'%xxx%availability%'	'%fixme% large %'
'%dependency%cycle%'	'%xxx%remove%'	'%todo%extensibility%'	'%xxx% large %'
'%todo%dependenc%'	'%fixme%remove%'	'%fixme%extensibility%'	'%future%maintenance%'
'%fixme%dependenc%'	'%todo%don%want%'	'%xxx%extensibility%'	'%todo%maintenance%'
'%xxx%dependenc%'	'%fixme%don%want%'	'%sacrifice%flexibility%'	'%fixme%maintenance%'
'%code%cop%from%'	'%xxx%don%want%'	'%todo%flexibility%'	'%xxx%maintenance%'
'%copied%code%'	'% fix % for %'	'%fixme%flexibility%'	'%todo%unused%'
'% any %reason%'	'% fix for %'	'%xxx%flexibility%'	'%fixme%unused%'
'%wrong%place%'	'%irritating%'	'%todo%scalability%'	'%xxx%unused%'
'%hairy%'	'%todo%duplicat%'	'%fixme%scalability%'	'%currently%unused%'
'%instead%could%'	'%fixme%duplicat%'	'%xxx%scalability%'	'%unused%delete%'
'%ugly%'	'%xxx%duplicat%'	'%security%compatibility%'	'%unused%currently%'
'%todo%avoid%'	'%why%not%'	'%security%never%'	'%such%bad%'
'%fixme%avoid%'	'%rethink%'	'%todo%security%'	'%todo%bad%'
'%xxx%avoid%'	'%rework%'	'%fixme%security%'	'%fixme%bad%'
'%should%avoid%'	'%pointless%'	'%xxx%security%'	'%xxx%bad%'
'%pathological%'	'% not %nice%'	'%todo%ambiguous%'	'%todo%clone%code%'
'%stolen%'	'%hack%'	'%fixme%ambiguous%'	'%fixme%clone%code%'
'%not%well%formed%'	'%only%developer%know%'	'%xxx%ambiguous%'	'%xxx%clone%code%'
'% no %sense%since%'	'% use % help%'	'%todo% big %'	'% dead %code%'
'%without%notic%'	'%hammer%'	'%fixme% big %'	'%crappy%design%'
'%brittle%'	'%todo%redundant%'	'%xxx% big %'	'%design%flaw%'
'%really%necessary%'	'%fixme%redundant%'	'% big % mess %'	'% todo% design %'
'%cares%'	'%xxx%redundant%'	'%clean%needed%'	'%fixme%design%'
'%no idea%'	'%for%some%reason%'	'%should%clean%'	'% xxx %design%'
'%idea?%'	'%alternatively%could%'	'%todo%clean%'	'%redesign%'
'%doing?%'	'%technically%'	'%fixme%clean%'	'%todo%magic%'
'%todo%elsewhere%'	'% forces %us%'	'%xxx%clean%'	'%fixme%magic%'
'%fixme%elsewhere%'	'%better%way%'	'%due%complex%'	'%xxx%magic%'
'%xxx%elsewhere%'	'%hard%coded%'	'%way%complex%'	'%smell%'