Authors' response for Using Natural Language Processing to Automatically Detect Self-Admitted Technical Debt

Editor Comments

Editor
Comments to the Author:
The reviewers all find novelty in the work of looking for technical debt in comments. However, there are several areas in which the manuscript requires improvement. In particular, the authors should:

* provide arguments or justification of why the studies focus on comments and do not validate the technical debt with the source code and whether it exhibits characteristics of technical debt. This point is related to the reviewers comments on choices not to compare to ways to assess technical debt based on source code.

* clarify how technical debt and requirements debt relate. The authors should carefully consider what information to fold in from the previous workshop paper to enable readers to have a self-contained means of understanding this manuscript.

* several reviewers commented on finding choices made for the random classifier (such as following the distribution of technical debt on the projects): these require clarification.

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Reviewers' Comments

Reviewer: 1

Public Comments (these will be made available to the author)
The paper presents an approach to detect technical debt automatically from source code comments based on NLP. The approach is used on a number of open source systems to train the NLP classifier and provide validation. The authors also discuss the prominent words used to indicate design and requirements technical debt and argue that their approach only needs a small training set.
The paper is easy to read and understand, written in a concise and clear manner. It tackles an important problem and reports on a well-design empirical study that provides sound evidence. However there are several points that need to be revised regarding the **motivation for the work**, the **design of the approach** and the **empirical study**.
Detailed comments per section follow.

Introduction
• (R1-1) Technical debt is not always incurred consciously. Martin Fowler was first to point this out.

Response:
Thank you for the comment. Indeed, we agree with the reviewer that technical debt can be incurred consciously and unconsciously. Clearly, in this work we focus on the self-admitted technical debt, which would fall under the technical debt that is consciously (or deliberately as Fowler calls it) incurred. We clarified this point in the paper and added the following text to the manuscript in the Introduction, paragraph 3:

"Technical debt can be deliberately or inadvertently incurred [5]. Inadvertent technical debt is technical debt that is taken on unknowingly. One example of inadvertent technical debt is architectural decay or architectural drift. To date, the majority of the technical debt work has focused on inadvertent technical debt [6]. On the other hand, deliberate technical debt, is debt that is incurred by the developer with knowledge that it is being taken on. One example of such deliberate technical debt, is self-admitted technical debt, which is the focus of our paper."

As part of this change, we also added the following citations:

1. M. Fowler. Technical debt quadrant. http://martinfowler.com/bliki/TechnicalDebtQuadrant.html, accessed: 2016-06-09.

2. R. L. Nord, I. Ozkaya, P. Kruchten, and M. Gonzalez-Rojas, "In search of a metric for managing architectural technical debt," in Software Architecture (WICSA) and European Conference on Software Architecture (ECSA), 2012 Joint Working IEEE/IFIP Conference on, 2012, pp. 91–100.

• (R1-2) Static analysis does help in detecting debt and is the more popular approach but there are also other techniques proposed that you seem to completely ignore. I know you want to compare your approach with techniques that focus on source code but you cannot ignore other ways of detecting debt, like architecture reviews.

Response:
Thank you for the comment. We mainly focused on the source code-related technical debt since our approach is related to source code comments. However, as the reviewer points out it is a good idea to also mention other ways that technical debt has been measured in the past. Therefore, we modified the manuscript to add the following text in Introduction, paragraph 4:

"Some of the approaches analyze the source code to detect technical debt, whereas other approaches leverage various techniques and artifacts, e.g., documentation and architecture reviews, to detect documentation debt, test debt or architecture debt (i.e., unexpected deviance from the initial architecture) [7], [8]."

As part of this change, we also added the following citations:

1. N. Alves, T. Mendes, M. G. de Mendona, R. Spinola, F. Shull, and C. Seaman, "Identification and management of technical debt: A systematic mapping study," Information and Software Technology, vol. 70, pp. 100–121, 2016.

2. L. Xiao, Y. Cai, R. Kazman, R. Mo, and Q. Feng, "Identifying and quantifying architectural debt," in Proceedings of the 38th International Conference on Software Engineering, 2016, pp. 488–498.

• (R1-3) You argue that detection based on source comments is better than source code, but you don't justify it well. First, I don't buy your third argument: why exactly is it more reliable to base on comments? Yes, developers write comments themselves but why does it make this approach more reliable? Also the first argument is not clear. So what if source code techniques require an AST? Such tools produce the end result in seconds so what is the problem exactly? In fact I am not at all convinced that detecting based on source comments is better at all – it is at best a complementary way.

Response:
Thank you for this comment. We have removed the third argument and emphasized the complementary role of detecting TD based on source comments. In addition, we supported the other two arguments with references from the related literature. The updated text can be found in the Introduction paragraphs 6 and 7:

“The recovery of technical debt through source code comments has two main advantages over traditional approaches based on source code analysis. First, it is more lightweight compared to source code analysis, since it does not require the construction of Abstract Syntax Trees or other more advanced source code representations. For instance, some code smell detectors that also provide refactoring recommendations to resolve the detected code smells [16], [17] generate computationally expensive program representation structures, such as program dependence graphs [18], and method call graphs [19] in order to match structural code smell patterns and compute metrics. On the other hand, the source code comments can be easily and efficiently extracted from source code files using regular expressions. Second, it does not depend on arbitrary metric threshold values, which are required in all metric-based code smell detection approaches. Deriving appropriate threshold values is a challenging open problem that has attracted the attention and effort of several researchers [20], [21], [22]. As a matter of fact, the approaches based on source code analysis suffer from high false positive rates [23] (i.e., they flag a large number of source code elements as problematic, while they are not perceived as such by the developers), because they rely only on the structure of the source code to detect code smells without taking into account the developers’ feedback, the project domain, and the context in which the code smells are detected.

However, relying solely on the developers’ comments to recover technical debt is not adequate, because developers might be unaware of the presence of some code smells in their project, or might not be well familiar with good design and coding practices (i.e., inadvertent debt). As a result, the detection of technical debt through source code comments can be only used as a complementary approach to existing code smell detectors based on source code analysis. We believe that self-admitted technical debt can be useful to prioritize the pay back of debt (i.e., develop a pay back plan), since the technical debt expressed in the comments written by the developers themselves is definitely more relevant to them.”

Approach
• (R1-4) The approach looks in general sound but the manual classification is a major issue. First, spending 185 hours to perform the manual classification is major effort. Anyone that wants to reuse your approach will have to retrain the classifier and perform this manual classification from scratch for a different domain, language, technology stack. This is a major hindrance towards the applicability of your approach.

Response:
Thank you for the comment. Indeed, the manual effort put into the approach is significant, however, the main purpose of the manuscript is to put forward an approach that can be trained using our manually classified dataset, so that such manual effort can be reduced in the future. As we have shown in the results of RQ1 and RQ3 that our NLP classifier performs well, even when tested on a project

that it has never been trained on in the past (RQ1), and when using small number of comments in the training dataset (RQ3). We also make our dataset publicly available so that others can easily build on our dataset or extend it.

As for the domain issue, we specifically chose our case studies to cover different domains. That said, we do not claim that our approach will generalize to all languages, domains, etc; achieving such generalizations is out of the scope of our paper and requires a different study specifically designed for such a purpose. To address this comment and clarify our intention here, we modified/added the following text to Sections 6 (Threats to Validity) and 7 (Conclusions and Future Work):

Section 6, last paragraph:

"To minimize the threat to external validity, we chose open source projects from different domains. That said, our results may not generalize to other open source or commercial projects, projects written in different languages, projects from different domains and/or technology stacks. In particular, our results may not generalize to projects that have a low number or no comments or that are written in a language other than English."

Section 7, paragraph 4:

"In addition, we plan to examine the applicability of our approach to more domains (than those we study in this paper) and software projects developed in different programming languages. Another interesting research direction that we plan to investigate in the future is the use of other machine learning techniques, such as active learning to reduce the number of labeled data necessary to train the classifier. This technique, if proved successful, can expand even further the horizon of projects that our approach can be applied."

• (R1-5) Second, inter-rate agreement measured according to Cohen's Kappa is 0.81 which is good but not impressive. This should be added to your threats to validity

Response:
Thank you for the comment. We made sure to discuss the inter-rater agreement in the threats to validity of the original submission. However, we believe that the reviewer's comment is related to the value achieved. After the reviewer's comment, we investigated the characterization of different Cohen's Kappa values. The literature shows that a Cohen's Kappa value of < 0.4 as being poor, 0.40 - 0.75 as being fair to good, and > 0.75 as excellent. To address this comment, we modified our original text in Section 2.4 and Section 6, paragraph 1:

Section 2.4:
"Lastly, we evaluate the level of agreement between both reviewers of the stratified sample by calculating Cohen's kappa coefficient [29]. The Cohen's Kappa coefficient has been commonly used to evaluate inter-rater agreement level for categorical scales, and provides the proportion of agreement corrected for chance. The resulting coefficient is scaled to range between -1 and +1, where a negative value means poorer than chance agreement, zero indicates exactly chance agreement, and a positive value indicates better than chance agreement [30]. The closer the value is to +1, the stronger the agreement. In our work, the level of agreement measured between the reviewers was of +0.81.

We also measured the level of agreement in the classification of design and requirement self-admitted technical debt individually. This is important because the stratified sample contains many more comments without self-admitted technical debt than the other types of debt, and therefore, the coefficient reported above could indicate that the reviewers are agreeing on what is not self-admitted technical debt, instead of agreeing on a particular type of debt. However, we achieved a level of agreement of +0.75 for design self- admitted technical debt, and +0.84 for requirement self-admitted technical debt. According to Fleiss [31] values larger than +0.75 are characterized as excellent agreement."

Section 6:
"Like any human activity, our manual classification is subject to personal bias. To reduce this bias, we took a statistically significant sample of our classified comments and asked a Master's student, who is not an author of the paper, to manually classify them. Then, we calculate the Kappa's level of agreement between the two classifications. The level of agreement obtained was +0.81, which according to Fleiss [31] is characterized as an excellent inter- rater agreement (values larger than +0.75 are considered excellent). Nevertheless, due to the irregular data distribution of our significant sample (which has many more comments without technical debt, than comments with the other classes of debt), we also measured Kappa's level of agreement for design and requirement self-admitted technical debt separately. The level of agreement obtained for design and requirement self-admitted technical debt was +0.75 and +0.84, respectively."

As part of this change, we also added the following citation:

1. J. Fleiss, "The measurement of interrater agreement," Statistical methods for rates and proportions., pp. 212–236, 1981.

• (R1-6) The selected OSS projects are at most a couple hundred thousands SLOC. Does this pose a threat to the external validity? Would your approach work on larger systems? Also please provide details on the application domains and explain in your threats to validity whether you can generalize to other application domains.

Response:
Thank you for the comment. As shown in Table 1, our projects range in size between ~81K - ~228K SLOC. This is comparable to other technical debt-related studies. For example, in [46], the authors study 2 projects that are 35K and 45K LOC, another study [47] used 12 subject systems that range in size between ~25K - ~81K. Therefore, we believe that our studied systems are in line with prior work. As for whether our approach would work on larger systems, we do not see any reason why the approach would not work on larger systems. The real question to consider however, is the quantity and quality of comments in these system, rather than their size. We mention that the quantity and quality of comments is a key component that may affect our approach. The following text in Section 6, paragraph 2:

"When performing our study, we used well-commented Java projects. Since our approach heavily depends on code comments, our results and performance measures may be impacted by the quantity and quality of comments in a software project."

As for the last part of the comment, we added the domain description for each application in Section 2.1, paragraph 1:

"Ant is a build tool written in Java, ArgoUML is an UML modeling tool that includes support for all standard UML 1.4 diagrams, Columba is an email client that has a graphical interface with wizards and internationalization support, EMF is a modeling framework and code generation facility for building tools and other applications, Hibernate is a component providing Object Relational Mapping (ORM) support to applications and other components, JEdit is a text editor written in Java, JFreeChart is a chart library for the Java platform, JMeter is a Java application designed to load functional test behavior and measure performance, JRuby is a pure-Java implementation of the Ruby programming language and SQuirrel SQL is a graphical SQL client written in Java."

Regarding the generalizability of our approach, we believe that this is related to comment R1-4 and has been addressed in that comment.

[46] N. Zazworka, M. A. Shaw, F. Shull, and C. Seaman, "Investigating the impact of design debt on software quality," in Proceedings of the 2nd International Workshop on Managing Technical Debt, 2011, pp. 17–23.

[47] F. Fontana, V. Ferme, and S. Spinelli, "Investigating the impact of code

smells debt on quality code evaluation," in Proceedings of the 3rd International Workshop on Managing Technical Debt, 2012, pp. 15–22.

Case Study results

• (R1-7) When formulating RQ1, do you consider that identifying technical debt is the same as predicting it? Also what exactly does effectiveness mean in this case?

Response:
Thank you for the comment. Indeed, we agree with the reviewer that identifying and predicting technical debt are distinct things, and should therefore be addressed as such. While predicting technical debt is related to time (using older debt to predict future debt), identifying technical debt is related to distinguish between the different types of debt. Thus, our approach is about identifying self-admitted technical debt. To address the reviewer comment we modified the wording of RQ1 to make it clearer as follows:

"RQ1. Is it possible to more accurately detect self-admitted technical debt using NLP techniques?"

As for what we mean by effectiveness, in this case we would like our approach to identify the SATD comments with accuracy that is better than the state-of-the-art today (which is using comment patterns). To address this comment we clarified our working throughout the paper, and in particular, we added the following clarification in section 3 paragraph 3:

"Therefore, we want to determine if NLP techniques such as, the maximum entropy classifier, can help us surpass these limitations and outperform the accuracy of the current state-of-the-art."

• (R1-8) I find the improvement over the comment patterns approach convincing (for design debt), but the comparison with the random approach (for requirements debt) is really not impressive. The F1-measure looks fine without making this comparison. This 18x improvement sounds like an oversell considering you only compare to the random classifier.

Response:
Thank you for the comment. Due the fact that self-admitted technical debt entries are very few in the studied dataset, the random classifier F1-measure serves as a lower bound baseline. Our intention when comparing our approach to the baseline is to make sure that we are at least better than this lower bound. That said, we do see the reviewer's point about the 18X improvement being an oversell, since it is comparing to a lower bound. Therefore, we modified the manuscript removing the reference to the 18x improvement, and instead

comparing to the state-of-the-art only. The text in the conclusion box for RQ1 has been updated as follows:

"We find that our NLP-based approach, is more accurate in identifying self-admitted technical debt comments compared to the current state-of-art. We achieved an average F1-measure of 0.620 when identifying design debt (an average improvement of 2.3× over the state-of-the- art approach) and an average F1-measure of 0.403 when identifying requirement debt (an average improvement of 6× over the state-of-the-art approach)."

• (R1-9) Also, why wasn't the comment patterns approach not able to detect any requirements debt?

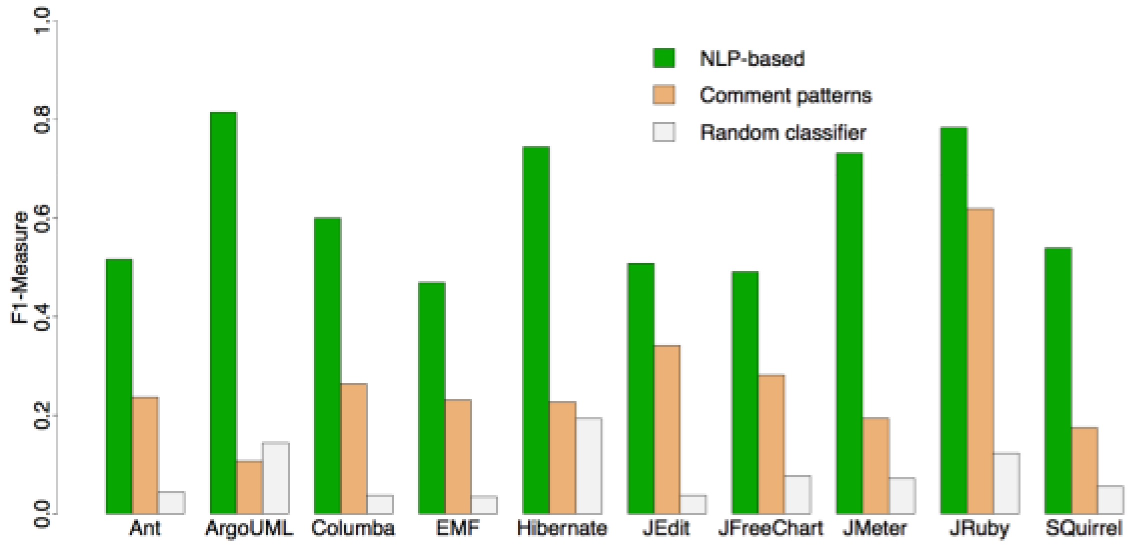
Response:
Thank you for the comment. To give a proper answer to this comment we revisited the experiment that was made to measure the performance of the comment patterns approach while identifying requirement technical debt. We found an issue in our scripts related to the case of the words in the comment patterns, which impacted the detection of the comment patterns approach. We resolved the issue and double checked all of our scripts to make sure the results are correct. After doing so, we find that the comment patterns approach is able to detect some requirement debt in 3 projects. Although it still performs poorly, it is better than being unable to detect any requirement debt.
To address this comment, we modified our original text in Section 3, paragraph 10:

"Similarly, the last five columns of Table 2 show the F1-measure performance of the three approaches, and the improvement achieved by our approach over the two other approaches. The comment patterns approach was able to identify requirement self-admitted technical debt in only 3 of the 10 analyzed projects. A possible reason for the low performance of the comment patterns in detecting requirement debt is that the comment patterns do not differentiate between the different types of self-admitted technical debt. Moreover, since most of the debt is design debt, it is possible that the patterns tend to favor the detection of design debt."

As a result of this change, we also updated all of the related tables and figures, in particular, we updated: section 3 Table 2, section 3 Figure 2a, section 3 Figure 2b, appendix Tables 7 and 8.

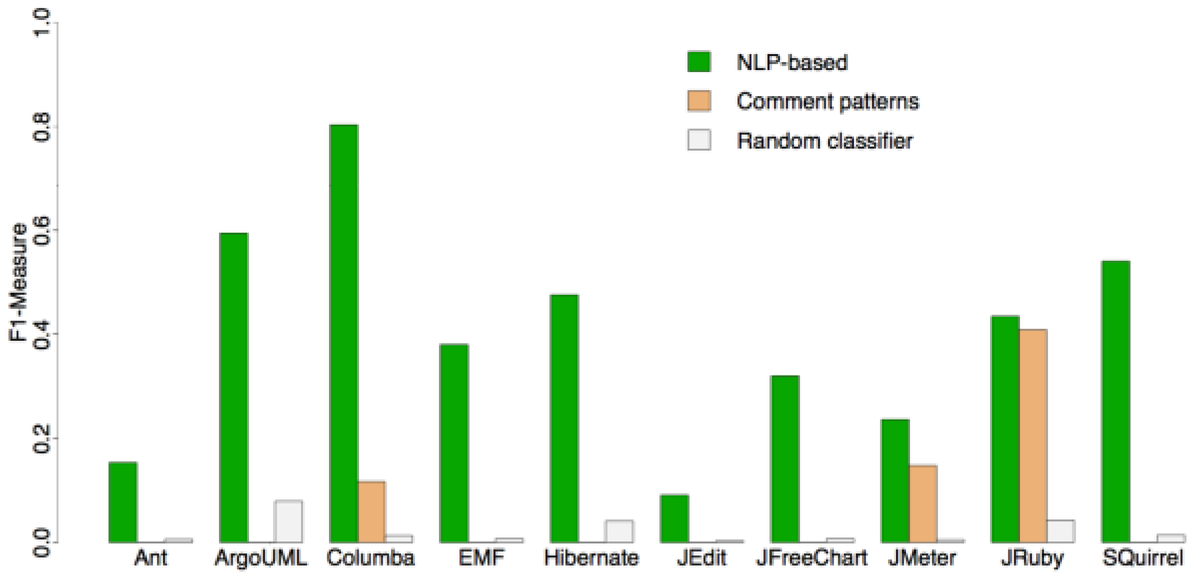
TABLE 2
Comparison of F1-measure between the NLP-based, the Comment Patterns and the Random Baseline Approaches for Design and Requirement Debt

Project	Design debt					Requirement debt				
	Our approach	Comment patterns	Random classifier	IMP over comment patterns	IMP over random classifier	Our approach	Comment patterns	Random classifier	IMP over comment patterns	IMP over random classifier
Ant	0.517	0.237	0.044	2.1×	11.7 ×	0.154	0.000	0.006	-	25.6×
ArgoUML	0.814	0.107	0.144	7.6×	5.6 ×	0.595	0.000	0.079	-	7.5 ×
Columba	0.601	0.264	0.037	2.2×	16.2 ×	0.804	0.117	0.013	6.8 ×	61.8×
EMF	0.470	0.231	0.034	2.0×	13.8 ×	0.381	0.000	0.007	-	54.4×
Hibernate	0.744	0.227	0.193	3.2×	3.8 ×	0.476	0.000	0.041	-	11.6×
JEdit	0.509	0.342	0.037	1.4×	13.7 ×	0.091	0.000	0.003	-	30.3×
JFreeChart	0.492	0.282	0.077	1.7×	6.3 ×	0.321	0.000	0.007	-	45.8×
JMeter	0.731	0.194	0.072	3.7×	10.1 ×	0.237	0.148	0.005	1.6 ×	47.4×
JRuby	0.783	0.620	0.123	1.2×	6.3 ×	0.435	0.409	0.043	1.0 ×	10.1×
SQuirrel	0.540	0.175	0.055	3.0×	9.8 ×	0.541	0.000	0.014	-	38.6×
Average	0.620	0.267	0.081	2.3×	7.6 ×	0.403	0.067	0.021	6.0 ×	19.1×



(a) Design Debt

Fig. 2. Visualization of the F1-measure for Different Approaches



(b) Requirement Debt

TABLE 8
Detailed Comparison of F1-measure Between the NLP-based, the Comment Patterns and the Random Baseline Approaches for Design Debt

Project	NLP-based			Comment Patterns			Random Baseline		
	Precision	Recall	F1 measure	Precision	Recall	F1 measure	Precision	Recall	F1 measure
Ant	0.554	0.484	0.517	0.608	0.147	0.237	0.023	0.5	0.044
ArgoUML	0.788	0.843	0.814	0.793	0.057	0.107	0.084	0.5	0.144
Columba	0.792	0.484	0.601	0.800	0.158	0.264	0.019	0.5	0.037
EMF	0.574	0.397	0.470	0.647	0.141	0.231	0.018	0.5	0.034
Hibernate	0.877	0.645	0.744	0.920	0.129	0.227	0.12	0.5	0.193
JEdit	0.779	0.378	0.509	0.857	0.214	0.342	0.019	0.5	0.037
JFreeChart	0.646	0.397	0.492	0.507	0.195	0.282	0.042	0.5	0.077
JMeter	0.808	0.668	0.731	0.813	0.110	0.194	0.039	0.5	0.072
JRuby	0.798	0.770	0.783	0.864	0.483	0.620	0.07	0.5	0.123
SQuirrel	0.544	0.536	0.540	0.700	0.100	0.175	0.029	0.5	0.055

TABLE 9
Detailed Comparison of F1-measure Between the NLP-based, the Comment Patterns and the Random Baseline Approaches for Requirement Debt

Project	NLP-based			Comment Patterns			Random Baseline		
	Precision	Recall	F1 measure	Precision	Recall	F1 measure	Precision	Recall	F1 measure
Ant	0.154	0.154	0.154	0.000	0.000	0.000	0.003	0.5	0.006
ArgoUML	0.663	0.540	0.595	0.000	0.000	0.000	0.043	0.5	0.079
Columba	0.755	0.860	0.804	0.375	0.069	0.117	0.007	0.5	0.013
EMF	0.800	0.250	0.381	0.000	0.000	0.000	0.004	0.5	0.007
Hibernate	0.610	0.391	0.476	0.000	0.000	0.000	0.022	0.5	0.041
JEdit	0.125	0.071	0.091	0.000	0.000	0.000	0.001	0.5	0.003
JFreeChart	0.220	0.600	0.321	0.102	0.266	0.148	0.003	0.5	0.007
JMeter	0.153	0.524	0.237	0.000	0.000	0.000	0.003	0.5	0.005
JRuby	0.686	0.318	0.435	0.573	0.318	0.409	0.022	0.5	0.043
SQuirrel	0.657	0.460	0.541	0.000	0.000	0.000	0.007	0.5	0.014

• (R1-10) One thing you do not explain is what you consider as design debt vs. requirement debt. This is a threat to your construct validity.

Response:
Thank you for the comment. We explained what we consider design and requirement debt in our previous work, and this information was provided in the original text through a citation [15]. However, we agree with the reviewer that the paper needs to stand on its own, hence, we added the following text from our previous work to better explain and give examples of what we consider as design and requirement debt. The following text in section 2.4 paragraphs 3 – 7 has been added.

"Below, we provide definitions for design and requirement self-admitted technical debt, and some indicative comments to help the reader understand the different types of self-admitted technical debt comments.

Self-admitted design debt: These comments indicate that there is a problem with the design of the code. They can be comments about misplaced code, lack of abstraction, long methods, poor implementation, workarounds, or temporary solutions. Usually these kinds of issues are resolved through refactoring (i.e., restructuring of existing code), or by re- implementing existing code to make it faster, more secure, more stable and so forth. Let us consider the following comments:

> **"TODO: - This method is too complex, lets break it up" - [from ArgoUml]**
>
> **"/* TODO: really should be a separate class */" - [from ArgoUml]**

These comments are clear examples of what we consider as self-admitted design debt. In the above comments, the developers state what needs to be done in order to improve the current design of the code, and the payback of this kind of design debt can be achieved through refactoring. Al- though the above comments are easy to understand, during our study we came across more challenging comments that expressed design problems in an indirect way. For example:

> **"// I hate this so much even before I start writing it. // Re-initialising a global in a place where no-one will see it just // feels wrong. Oh well, here goes." - [from ArgoUml]**
>
> **"//quick & dirty, to make nested mapped p-sets work:" - [from Apache Ant]**

In the above example comments the authors are certain to be implementing code that does not represent the best solution. We assume that this kind of implementation will degrade the design of the code and should be avoided.

"// probably not the best choice, but it solves the problem of // relative paths in CLASSPATH" - [from Apache Ant]

"//I can't get my head around this; is encoding treatment needed here?" - [from Apache Ant]

The above comments expressed doubt and uncertainty when implementing the code and were considered as self- admitted design debt as well. The payback of the design debt expressed in the last four example comments can be probably achieved through the re-implementation of the currently existing solution.

Self-admitted requirement debt: These comments convey the opinion of a developer supporting that the implementation of a requirement is not complete. In general, requirement debt comments express that there is still missing code that needs to be added in order to complete a partially implemented requirement, as it can be observed in the following comments:

"/TODO no methods yet for getClassname" - [from Apache Ant]

"//TODO no method for newInstance using a reverse- classloader" - [from Apache Ant]

"TODO: The copy function is not yet * completely implemented - so we will * have some exceptions here and there.*/" - [from ArgoUml]
"TODO: This dialect is not yet complete. Need to provide implementations wherever Not yet implemented appears" - [from SQuirrel]

The citation mentioned and that was used to add this text is the following:

1. E. d. S. Maldonado and E. Shihab, "Detecting and quantifying different types of self-admitted technical debt," in Proceedings of the 7th International Workshop on Managing Technical Debt, 2015, pp. 9–15.

• (R1-11) If I look at the keywords from RQ2 I am really not sure how you classified requirements debt. The fact that you have the same keyword appearing in both design and requirements debt indicates you may not have a clear distinction. To make matters worse, what you seem to hint is that requirements debt concerns requirements not yet implemented in code. This is in contrast to the orthodox perception on technical debt (see P. Kruchten et al. Technical Debt: From Metaphor to Theory and Practice)

Response:
Thank you for the comment. We believe that the reviewer comment is related to the missing explanation about what we considered as design and requirement self-admitted technical debt. We hope that this issue is addressed through the previous comments, R1-10.

In P. Kruchten et al. Technical Debt: From Metaphor to Theory and Practice, the authors explain how the technical debt metaphor is getting traction over the years and how multiple authors have been using the metaphor to communicate "not quite right code". The authors express their concern about how the use (or abuse) of the metaphor could spread it too thin making the metaphor lose its communication power. More recently, N. Alves et al. in their paper, "Identification and management of technical debt: A systematic mapping study" defined requirement debt as:

> **"Requirements debt: Refers to trade-offs made with respect to what requirements the development team needs to implement or how to implement them. Some examples of this type of debt are: requirements that are only partially implemented, requirements that are implemented but not for all cases, requirements that are implemented but in a way that doesn't fully satisfy all the non-functional requirements (e.g. security, performance, etc.)"**

We believe that our definition of requirement debt is not in disagreement with the literature. That said, we agree with the reviewer that our original text may lead the reader to conclude that requirement debt is related to requirements not yet implemented in code instead of *partially* implemented requirements. To address this problem, we provide some indicative comments using the top-ranked features shown in Table 3 that constitute design and requirement debt in the following text in RQ2, paragraph 7.

"From Table 3 we observe that the top ranked textual features for design self-admitted technical debt, i.e., hack, workaround, yuck!, kludge and stupidity, indicate sloppy or mediocre source code quality. For example, we have the following comment that was found in JMeter:

"Hack to allow entire URL to be provided in host field"

Other textual features, such as needed?, unused? and wtf? are questioning the usefulness or utility of a specific source code fragment, as indicated by the following comment also found in JMeter:

"TODO: - is this needed?"

For requirement self-admitted technical debt, the top ranked features, i.e., todo, needed, implementation, fixme and xxx indicate the need to complete requirements in the future that are currently partially complete. An indicative example is the following one found in JRuby:

"TODO: implement, won't do this now"

Some of the remaining lower ranked textual features, such as convention, configurable and fudging also indicate potential incomplete requirements, as shown in the following comments:

“Need to calculate this... just fudging here for now” [from JEdit]

“could make this configurable” [from JFreeChart]

“TODO: This name of the expression language should be configurable by the user” [from ArgoUML]

“TODO: find a way to check the manifest-file, that is found by naming convention” [from Apache Ant]”

Please note in the aforementioned examples how TODO is used to express both design and requirement debt when used in combination with other words, or how the word need/needed changes the meaning of the comment when used with and without “?”.

We hope that the provided explanation and the modified text address this issue, however, if it has not, we are happy to incorporate any other changes the reviewers suggest.

Related citations:

1. P. Kruchten, R. L. Nord, and I. Ozkaya, “Technical debt: From metaphor to theory and practice.” Ieee software, vol. 29, 2012.

2. N. Alves, T. Mendes, M. G. de Mendonça, R. Spinola, F. Shull, and C. Seaman, “Identification and management of technical debt: A systematic mapping study,” Information and Software Technology, vol. 70, pp. 100–121, 2016.

Discussion
• (R1-12) The similarity of terms in requirements and design debt cannot be intuitively confirmed by looking at the top-ten terms from RQ2. There it looks like some terms (e.g. convention, configurable, apparently, fudging) are less similar than those for design debt. Can you explain that?

Response:
Thank you for the comment. In RQ2 we display the top-ten terms that were used to identify design and requirement debt. This means that these terms have the highest weight between all the other terms that were used during the classification process. The weight is given through the number of occurrences that a feature has in the training data. Moreover, the classification process is not based only on the top-ten terms, but on a combination of terms (as many as the classifier can match) to determine the class of the comment. Therefore, the top-

ten words do not necessarily need to be similar with each other or have a semantic overlap.

However, to provide more insight we highlighted in Table 3 the words that appear consistently in all top-10 lists extracted from each one of the training data sets (i.e., the first two words for design debt, and the first 5 words for requirement debt). We consider these words as more universal features compared to the others. Although the non-highlighted features still have large weights, they can be considered as more project specific. We also added the following text in the paper:

"It should be noted that the features highlighted in bold in Table 3 appear in all top-10 lists extracted from each one of the ten training datasets, and therefore can be considered as more universal/stable features compared to the others."

Threats to validity
• (R1-13) It seems you have confused internal validity. It concerns causality which you do not study in your paper. The threats you mention, like the bias during manual classification is a threat to construct validity.

Response:
Thank you for the comment. We revisited the threats to validity sections and marked the internal and construct validity in the manuscript as suggested by the reviewer.

• (R1-14) Please extend your discussion with threats to construct validity and reliability

Response:
Thank you for the comment. We added the following text in the manuscript on section 6 paragraphs 3 and 5 to address this comment.

"Considering the intentional misrepresentation of measures, it is possible that even a well commented project does not contain self-admitted technical debt. Given the fact that the developers may opt to not express themselves in the source code comments. In our study, we made sure that we choose case studies that are appropriately commented for our analysis.

Lastly, our approach depends on the correctness of the underlying tools we use. To mitigate this risk, we used tools that are commonly used by practitioners and by the research community, such as JDeodorant for the extraction of source code comments and for investigating the overlap with code smells (Section 4.4) and the Stanford Classifier for training and testing the max entropy classifier used in our approach."

Small Details

- “this is a dirty hack it’s better do to something” -> to do
- “”conjucture”

Response:
Thank you for catching these typos, we fixed them in the revised manuscript.

Reviewer: 2

Public Comments (these will be made available to the author)
This paper presents a NLP approach to detecting 'self-admitted technical debt', that is, comments in the code that confess to (presumably) the following code being debt-laden. The authors previously approached this with a word-bag model which identified TD using common terms (like "hack"). In this paper they extend the approach using several NLP techniques to create a classifier from their large gold-standard of manually labeled TD items. They show significant improvement over the previous approach and a random approach to classification. They also present some results showing sensitivity of the classifier to training set size, which is useful for industry applications.

• (R2-1) The paper is well written, aside from frequent reference to their earlier work [10].

Response:
Thank you for the comment. Indeed, there are multiple citations to this our prior work. The main reason is that this study was the first one to explore technical debt found in source code comments, and we use the approach suggested in this paper as our upper boundary baseline. That said, we agree with the reviewer that the frequent reference to this previous work should be decreased. We reworked the paper, in particular the introduction, the approach and the results sections. We also added more details from our prior work (to address comment R1-10 above), which also reduced the references to our prior work.

• (R2-2) The idea of detecting TD from code comments using NLP tools is novel and empirically demonstrated in the paper; a tool that is publicly available (for eg. in SonarQube) would be interesting to test with developers. However, there is no connection made between the authors' construct of self-admitted TD, with other notions of TD. Therefore, the study is really just a labeling exercise using categories defined in another paper, then the use of an off-the-shelf NLP tool. To demonstrate a useful contribution, the work should try to validate the labeling (and subsequent classifier) against either other static analysis tools, or with working developers. That way readers will know whether the classifier is actually detecting TD or not.

Response:
Thank you for the comment. Indeed, comparing our approach to detect self-admitted technical with other static analysis tools is a very good idea. To address this comment we compared the technical debt files that were detected by our approach and the files detected by a static analysis tool. More specifically, we used JDeodorant to detect three well know code smells (i.e., long method, feature envy and god class) that are commonly considered as technical debt.

We also tried a metric-based code smell detector "https://github.com/diegocedrim/code-smells-detector" which is one of the very few available tools that supports the detection of Feature Envy, Long Method, and God/Blob Class and can be executed from command-line without depending on an IDE, and thus was ideal for our experiments. However, we found out that it was flagging too many files as problematic, especially for Feature Envy code smell.

After a careful inspection of the tool's code, we realized that the implementation for Feature Envy is not correct, because it flags a method as feature envy if the total number of dependencies to other classes is more than the dependencies to the class the method currently belong to.

The correct implementation would need to count the number of dependencies individually for each external class, and flag the method as Feature Envy if the number of dependencies to one of the external classes is more than the number of internal dependencies. Due to this implementation error, we considered that the tool is not reliable enough, and thus we used JDeodorant. We present and discuss the results in subsection 4.4 under the Discussion section.

"Investigating the Overlap Between Technical Debt Found in Comments and Technical Debt Found by Static Analysis Tools

Considering the intentional misrepresentation of measures, it is possible that even a well commented project does not contain self-admitted technical debt. Given the fact that the developers may opt to not express themselves in source code comments. In our study, we made sure that we choose case studies that are appropriately commented for our analysis. Thus far, we analyzed technical debt that was expressed by developers through source code comments. However, there are other ways to identify technical debt, such as architectural reviews, documentation analysis, and static analysis tools. To date, using static analysis tools is the most established approach to identify technical debt in the source code. In general, static analysis tools parse the source code of a project to calculate metrics and identify possible object oriented design violations, also known as code smells, anti-patterns, or design technical debt, based on some fixed metric threshold values.

In this subsection, we analyze the overlap between what our NLP-based approach identifies as technical debt and what a static analysis tool identifies as technical debt. We selected JDeodorant as the static analysis tool, since it sup- ports the detection of three popular code smells, namely Long Method, God Class, and Feature Envy. We avoided the use of metric-based code smell detection tools, because they tend to have high false positive rates and flag a large portion of the code base as problematic [23]. On the other hand, JDeodorant detects only actionable code smells (i.e., code smells for which a behavior-preserving refactoring can be applied to resolve them), and does not rely on any metric

thresholds, but rather applies static source code analysis to detect structural anomalies and suggest refactoring opportunities to eliminate them.

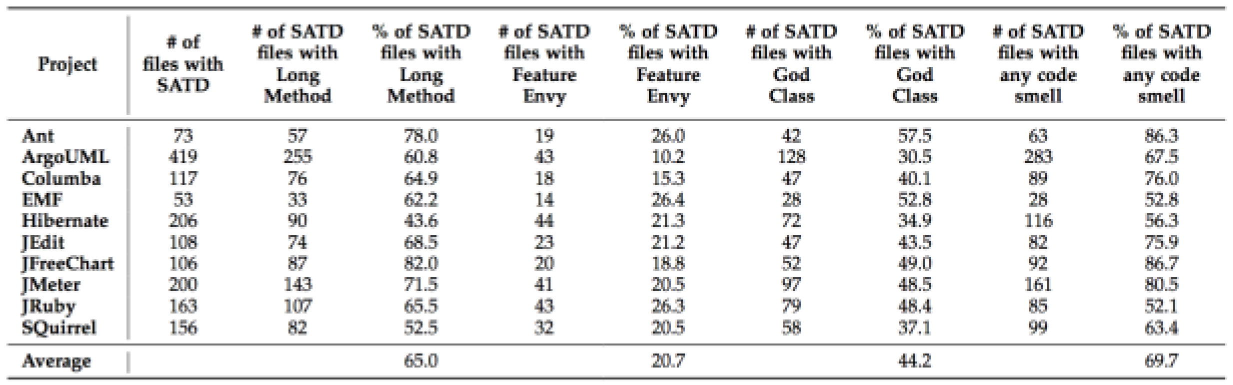
First, we analyzed our 10 open source projects using JDeodorant. The result of this analysis is a list of Java files that were identified having at least one instance of the Long Method, God Class, and Feature Envy code smells. These code smells have been extensively investigated in the literature, and are considered to occur frequently [40], [41]. Second, we created a similar list containing the files that were identified with self-admitted technical debt comments. Finally, we examined the overlap of the two lists of files. It should be emphasized that we did not examine if the self-admitted technical debt comments actually discuss the detected code smells, but only if there is a co-occurrence at file-level.

Table 7 provides details about each one of the projects used in our study. The columns of Table 7 present the total number of files with self-admitted technical debt, followed by the number of files containing self-admitted technical debt comments and at least one code smell instance, along with the percentage over the total number of files with self- admitted technical debt, for Long Method, Feature Envy, God Class, and all code smells combined, respectively.

JMeter, for example, has 200 files that contain self- admitted technical debt comments, and 143 of these files also contain at least one Long Method code smell (i.e., 71.5%). In addition, we can see that 20.5% of the files that have self-admitted technical debt are involved in Feature Envy code smells, and 48.5% of them are involved in God Class code smells. In summary, we see that 80.5% of the files that contain self-admitted technical debt comments are also involved in at least one of the three examined code smells.

We find that the code smell that overlaps the most with self-admitted technical debt is Long Method. Intuitively, this is expected, since Long Method is a common code smell and may have multiple instances per file, because it is computed at method level. The overlap between files with self-admitted technical debt and Long Method ranged from 43.6% to 82% of all the files containing self-admitted technical debt comments, and considering all projects, the average overlap is 65%. In addition, 44.2% of the files with self-admitted technical debt comments are also involved in God Class code smells, and 20.7% in Feature Envy code smells. Taking all examined code smells in consideration we find that, on average, 69.7% of files containing self-admitted technical debt are also involved in at least one of the three examined code smells.

TABLE 7
Overlap between the files containing self-admitted technical debt and the files containing code smells as detected by JDeodorant



Project	# of files with SATD	# of SATD files with Long Method	% of SATD files with Long Method	# of SATD files with Feature Envy	% of SATD files with Feature Envy	# of SATD files with God Class	% of SATD files with God Class	# of SATD files with any code smell	% of SATD files with any code smell
Ant	73	57	78.0	19	26.0	42	57.5	63	86.3
ArgoUML	419	255	60.8	43	10.2	128	30.5	283	67.5
Columba	117	76	64.9	18	15.3	47	40.1	89	76.0
EMF	53	33	62.2	14	26.4	28	52.8	28	52.8
Hibernate	206	90	43.6	44	21.3	72	34.9	116	56.3
JEdit	108	74	68.5	23	21.2	47	43.5	82	75.9
JFreeChart	106	87	82.0	20	18.8	52	49.0	92	86.7
JMeter	200	143	71.5	41	20.5	97	48.5	161	80.5
JRuby	163	107	65.5	43	26.3	79	48.4	85	52.1
SQuirrel	156	82	52.5	32	20.5	58	37.1	99	63.4
Average			65.0		20.7		44.2		69.7

As part of this change, we also added the following citations:
1. F. A. Fontana, J. Dietrich, B. Walter, A. Yamashita, and M. Zanoni, "Antipattern and code smell false positives: Preliminary conceptualization and classification," in IEEE 23rd International Conference on Software Analysis, Evolution, and Reengineering, 2016, pp. 609– 613.

2. S.M.Olbrich, D.S.Cruzes, and D.I.K. Sjberg,"Are all code smells harmful? A study of god classes and brain classes in the evolution of three open source systems," in Software Maintenance (ICSM), 2010 IEEE International Conference on, Sept 2010, pp. 1–10.

3. D. I. Sjoberg, A. Yamashita, B. C. Anda, A. Mockus, and T. Dyba, "Quantifying the effect of code smells on maintenance effort," IEEE Transactions on Software Engineering, vol. 39, no. 8, pp. 1144– 1156, 2013.

== Major comments to authors

• (R2-3) It would be nice to have something more concrete on the relationship with [10]. For instance the process overview is nearly identical except for the label NLP classification. For historical record, it would be useful to have both studies amalgamated here (which I think is permissible given copyright). The most glaring omission in my view is the criteria by which some comment is classified as requirements vs design debt. I think readers would be curious to know how you distinguish between these two types, and from the other 3 types. (e.g. P25 of this submission). There is certainly some room for debate in how you are classifying them. Perhaps another option is to link to the training manual you provided coder 2 for his/her task.

Response:
Thank you for the comment. We agree with the reviewer that defining self-admitted technical debt and the criteria that we used when classifying them is a must, and that the journal paper should stand on its own instead of relying on references that could be ignored or even unpractical for the reader. Reviewer 1 had a similar comment (R1-10). Please refer to R1-10 or to section 2.4 paragraphs 3 – 6 in the manuscript to see how we address this comment.

• (R2-4) Finally, you repeatedly refer to study [10] as 'state-of-the-art' which is true, in as much as it represents the only other study to my knowledge approaching the issue of identifying TD through code comments. But the paper would be improved by merging the two papers, in my view, and I'm curious why you chose to divide them.

Response:
Thank you for the comment. The reference that the reviewer is mentioning is the previous work by Potdar and Shihab published on 2014. In their study the authors devised 62 comment patterns (i.e., words and short phases) from source code comments extracted from 5 open source projects. To date, these 62 comment patterns, are the "state-of-the-art" on detection of self-admitted technical debt. That said, we think that the reviewer is really talking about our other work, by Maldonado and Shihab published in 2015 (reference [11] in the original submitted manuscript), that has much more in common with the current work.

That said, we initially decided to divide them since one was about the dataset and determining what types of self-admitted technical debt are most common, whereas this journal paper is more about using NLP to detect self-admitted technical debt.

Nevertheless, taking into consideration the reviewer's comment, we merged some parts from the previous work to make the journal paper stand on its own. We consider that this was achieved by addressing comments R1-10 and consequently R2-3. We hope that the provided explanation addressed this issue, however, if it has not, we are happy to incorporate any other changes the reviewers suggest.

• (R2-5) F-measure is the harmonic mean, which implies both P and R are valued equally. However, there are good reasons for thinking this is not the right model for software problems (see e.g. Berry et al REFSQ 2012 "The case for dumb RE tools") and that instead recall should be the target. In this case, one use for the tool is to find code with technical debt. Would a dev rather see all the code with TD, at the expense of some more noise, or greatly reduce the noise and miss some actual TD? My instinct tells me the latter. I would like to see your view on the subject. In any case a naive 50/50 split like F1 seems incorrect. From Appendix table 7 it seems like your approach (in this paper and the previous one) favor high precision vs high recall. Can you explain why this is desirable? Perhaps the case made in Sadowski's ICSE2014 paper on industrial static analysis tools (now called Shipshape), namely, devs hate the noise.

Response:
Thank you for the comment. In Berry et al. "The Case for Dumb Requirement Engineering Tools" the authors explain how four different types of NLP tools are used to analyze requirement documents. Extracting requirements from

documentation is considered as a tedious and error prone task for analysts, and the assistance of tools is highly appreciated. The authors argue that tools with high recall (few false negatives) is actually preferable than tools with high precision (few false positives). Their reasoning is that it is easier for an analyst to manually eliminate false positives identified by the tool than finding the possible missing false negatives by themselves. Therefore, a tool providing 100% recall would prevent a fully manual effort to extract requirement as the analyst should be concerned only on eliminating the false positives.

Berry et al. presents solid reasoning that makes perfect sense when extracting requirements from existing documentation. In this specific scenario it is necessary to identify all requirements that it is contained in the analyzed documents. However, when dealing with technical debt maters tend to be different, as the reviewer points out. In
A. Bessey et al. "A few billion lines of code later: Using static analysis to find bugs in the real world" the authors document important challenges that they faced while developing and commercializing bug finding tools. Among other things, they discuss the implications of having a high number of false positives, and how this is not desired. For example, they say that true bugs get lost in false bugs, people will ignore the tool and ultimately will lost trust on it. More recently, Ernest et al. in "Measure It? Manage It? Ignore It? Software Practitioners and Technical Debt" conducted a survey of 1,831 participants that included software engineers, architects and developers from three large organizations. They report that the adoption of tools and approaches to identify and manage technical debt is uncommon. One of the reasons is that false positives produces a lot of noise and is cumbersome to deal with. Sadowski et al. "Tricoder: Building a Program Analysis Ecosystem" offers many insights on why static analysis tools are often not used effectively in practice, and again, false positives appear as not desired result.

The way that we envision the approach being applied follows the line of thought of Bessey, Ernest and Sadowski which favors precision instead of recall (but of course achieving high values of precision and recall is desirable). That said, we agree with the reviewer point that some readers could benefit of an approach that favors recall. To address this comment we added the following text in the discussion section 4.3 paragraph 4.

"According to previous work, developers hate to deal with false positives (i.e., low precision) [33], [34], [35]. Due to this fact, we choose to present our results in this study using the maximum entropy classifier, which has an average precision of 0.716 throughout all projects. However, favoring recall over precision by using the Naïve Bayes classifier might still be acceptable, if a manual process to filter out false positives is in place, as reported by Berry et al. [36]."

Also, we mention in the results section that one of the main advantages of our NLP-based technique is that we improve recall over the comment patterns approach, which achieves decent precision but poor recall.

The citation mentioned and that was used to add this text is the following:

1. A. Bessey, K. Block, B. Chelf, A. Chou, B. Fulton, S. Hallem, C. Henri-Gros, A. Kamsky, S. McPeak, and D. Engler, "A few billion lines of code later: Using static analysis to find bugs in the real world," Commun. ACM, pp. 66–75, 2010.

2. N. A. Ernst, S. Bellomo, I. Ozkaya, R. L. Nord, and I. Gorton, "Measure it? manage it? ignore it? software practitioners and tech- nical debt," in Proceedings of the 10th Joint Meeting on Foundations of Software Engineering, 2015, pp. 50–60.

3. C. Sadowski, J. v. Gogh, C. Jaspan, E. Soderberg, and C. Win- ter, "Tricorder: Building a program analysis ecosystem," in 2015 IEEE/ACM 37th IEEE International Conference on Software Engineer- ing, 2015, pp. 598–608.

4. D. Berry, R. Gacitua, P. Sawyer, and S. F. Tjong, The Case for Dumb Requirements Engineering Tools, 2012.

• (R2-6) The random classifier puzzles me. It sounds like you have it randomly bucketing something as TD based on the underlying model you derive from the manual labeling. E.g. if the source dataset had 6% TD, 6% of the time (randomly) this classifier assigns the TD label. But why should the random classifier have to know the underlying distribution? What would you get if you set it to 50%? What I am saying is that the random classifier in your approach has this prior that in reality a naive classifier wouldn't get. And at 50% I suspect the recall would be much closer to the NLP approach. To be honest the discussion on page 6 was very unclear on how you ran this. I don't see why it needs some particular calculation for precision or recall, since you will simulate it just like a regular classifier, then measure the P/R based on the classification results.

Response:
Thank you for the comment. First off, we would like to clarify that the random classifier is there to serve as a lower baseline that we need to ensure we surpass. In the case of an imbalanced dataset, like ours, the precision of a random classifier would be the same as the occurrence of the class of interest. In a balanced dataset, i.e., 50-50 split, then the precision of the random classifier would be 50%.

We hope this answers the comment by the reviewer, but if it does not, we would be happy to clarify more.

• (R2-7) Finally, I expected to see in the results something that looked at TD vs non-TD (that is, no categories). The reasoning for this is that assuming the categories are invalid, even knowing there is TD of some kind would be helpful; it would therefore be interesting to know if performance changes.

Response:
Thank you for the comment. We designed our experiment to distinguish between different types of self-admitted technical debt because it enables each type of debt to be handled in a specific way. However, we do agree with the reviewer that it is worthwhile knowing if technical debt exists or not. To address this comment we added experiments that we present in subsection 4.2 under the Discussion section.

"Distinguishing Self-Admitted Technical Debt from Non-Self-Admitted Technical Debt Comments

So far, we analyzed the performance of our NLP-based approach to identify distinct types of self-admitted technical debt (i.e., design and requirement debt). However, a simpler distinction between self-admitted technical debt and non-debt comments can also be interesting in the case those fine- grained classes of debt are not considered necessary by a user of the proposed NLP-based detection approach. An- other reason justifying such a coarse-grained distinction is that the cost of building a training dataset with fine-grained classes of debt is more expensive, mentally challenging, and subjective than building a training dataset with just two classes (i.e., comments with and without technical debt).

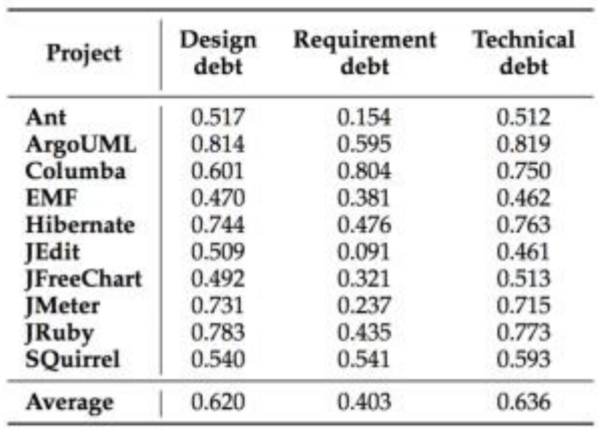
In order to compute the performance of our NLP-based approach using only two classes (i.e., comments with and without technical debt), we repeat RQ1 and RQ2 with modified training and test datasets. First, we take all design and requirement self-admitted technical debt comments and label them with a common class i.e., technical debt, and the remaining comments we kept them labeled as without technical debt. Second, we run the maximum entropy classifier in the same leave-one-out cross-project validation fashion, using the comments of 9 projects to train the classifier and the comments from the remaining project to test the classifier. We repeat this process for each of the ten projects and compute the average F1-measure. Lastly, we analyze the textual features used to identify the self-admitted technical debt comments.

Table 5 compares the F1-measure achieved when detecting design debt, requirement debt, separately and when detecting both combined in a single class. As we can see, the performance when detecting technical debt is very similar with the performance of the classifier when detecting design debt. This is expected, as the majority of technical debt comments in the training dataset are labeled with the design debt class. Nevertheless, the performance achieved when detecting design debt was surpassed in the projects where the classifier

performed well in detecting requirement debt, for example, in Columba (0.601 vs. 0.750) and SQuirrel SQL (0.540 vs. 0.593).
We find that the average performance when detecting design and requirement self-admitted technical debt combined is better (0.636) than the performance achieved when detecting them individually (0.620 and 0.403 for design and requirement debt, respectively).

Table 6 shows a comparison of the top-10 textual features used to detect design and requirement debt comments separately, and those used to detect both types of debt combined in a single class. When analyzing the top-10 textual features used to classify self-admitted technical debt, we find once more, a strong overlap with the top-10 textual features used to classify design debt. The weight of the features is attributed in accordance to the frequency that each word is found in the training dataset, and therefore, the top- 10 features tend to be similar with the top-10 design debt features, since design debt comments represent the majority of self-admitted technical debt comments in the dataset.

TABLE 5
F1-measure Performance Considering Different Types of Self-admitted Technical Debt



Project	Design debt	Requirement debt	Technical debt
Ant	0.517	0.154	0.512
ArgoUML	0.814	0.595	0.819
Columba	0.601	0.804	0.750
EMF	0.470	0.381	0.462
Hibernate	0.744	0.476	0.763
JEdit	0.509	0.091	0.461
JFreeChart	0.492	0.321	0.513
JMeter	0.731	0.237	0.715
JRuby	0.783	0.435	0.773
SQuirrel	0.540	0.541	0.593
Average	0.620	0.403	0.636

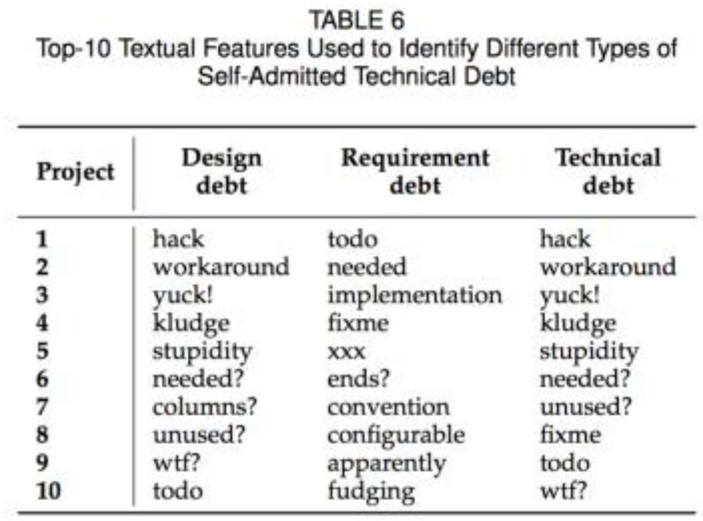


TABLE 6
Top-10 Textual Features Used to Identify Different Types of Self-Admitted Technical Debt

Project	Design debt	Requirement debt	Technical debt
1	hack	todo	hack
2	workaround	needed	workaround
3	yuck!	implementation	yuck!
4	kludge	fixme	kludge
5	stupidity	xxx	stupidity
6	needed?	ends?	needed?
7	columns?	convention	unused?
8	unused?	configurable	fixme
9	wtf?	apparently	todo
10	todo	fudging	wtf?

• (R2-8) I don't understand why in S 2.4, for the coding agreement portion, you selected a random dataset that nearly matched the breakdown of the real world datasets. This results in a very low number of actual true positives (e.g., only 1 comment of the 659 was doc debt). So when we calculate Kappa, my concern is that kappa here is really measuring a comment is "debt or non-debt", and not the specific categories. In other words it does not help us assess whether what coder 1 is calling "requirements debt" is also what coder 2 calls requirements debt. A mitigation here is to include category specific kappa scores, or to use a non-representative sample (I don't get why this is important to the task).

Response:
Thank you for the comment. Indeed, we kept the dataset as close as possible to a real world scenario. The intention here is to validate the dataset as a whole, decreasing the bias towards a specific type technical debt. For instance, before the classification, the student was not told the expected quantity of each debt in the dataset. This is a positive reinforcement that we were also able to identify what is not technical debt correctly.

However, we agree with the reviewer that focusing only on different types of self-admitted technical debt is also a viable option. We also agree with the reviewer's concern that in our case Kappa could be in reality measuring debt or non-debt comments. To address this comment we added/modified the text in section 2.4 and the threats to validity with category specific kappa scores for design and requirement self-admitted technical debt.

Section 2.4, last paragraph:

"We also measured the level of agreement in the classification of design and requirement self-admitted technical debt individually. This is important because the stratified sample contains many more comments without self-admitted

technical debt than the other types of debt, and therefore, the coefficient reported above could indicate that the reviewers are agreeing on what is not self-admitted technical debt, instead of agreeing on a particular type of debt. However, we achieved a level of agreement of +0.75 for design self- admitted technical debt, and +0.84 for requirement self- admitted technical debt. According to Fleiss [31] values larger than +0.75 are characterized as excellent."

Threats to Validity, first paragraph:

"Like any human activity, our manual classification is subject to personal bias. To reduce this bias, we took a statistically significant sample of our classified comments and asked a Master's student, who is not an author of the paper, to manually classify them. Then, we calculate the Kappa's level of agreement between the two classifications. The level of agreement obtained was 0.81, which according to Fleiss [31] is characterized as an excellent inter-rater agreement (values larger than +0.75 are considered excellent). Nevertheless, due to the irregular data distribution of our significant sample (which has many more comments without technical debt, than comments with the other classes of debt), we also measured Kappa's level of agreement for design and requirement self-admitted technical debt separately. The level of agreement obtained for design and requirement self- admitted technical debt was +0.75 and +0.84, respectively."

As part of this change, we also added the following citation:

[31] J. Fleiss, "The measurement of interrater agreement," Statistical methods for rates and proportions., pp. 212–236, 1981.

• (R2-9) Your text frequently says "NLP classifier" (and you mean max entropy classifier). A decision tree would be interesting here, given your RQ2 and the problem of what words are important. I would think the decision tree could present this quite nicely. There are other classifiers to attempt too (and something like Weka would give you access to all of them and let you see which is most suitable). Other SE papers on NLP, e.g. Andi Marcus or Abram Hindle in topic modeling, discuss these extensively. The paper would benefit from presenting other ways of doing the classification. The state of the art in the SE/NLP world is moving to a deeper consideration of these questions - you would benefit from having discussions with the linguistics folks at your institution. (I see later you do discuss 2 others in Section 4.2. But now I see you discounting Naive Bayes although it does better on recall - see above for why this might well be fine). The related work covers some of the applicable work, but I'm not sure just because the subject matter is different - e.g. traceability vs self-admitted debt - that the underlying NLP approach is not still relevant for comparison. Some more discussion of your classifier and why it makes sense in the context of the domain is merited.

Response:
Thank you for the comment. Indeed, what we meant by "NLP classifier" was max entropy classifier. We modified all occurrences of "NLP classifier" in the manuscript to the more appropriate term as pointed out.

As the reviewer noticed, we discuss 2 other ways of doing the classification in the discussion subsection 4.3. Also, we agree with the reviewer that we were discounting Naïve Bayes because it performed poorly in precision. We believe that we addressed this comment by responding to comment R2-5 where we present the case why developers prefers precision over recall, and by explaining the scenario where recall over precision could be interesting.

Also, for the remaining of the comment we agree that more discussion of our classifier is, indeed merited, and how to choose a specific classifier kind as well. To address this comment we added the following text in subsection 4.3 paragraph 6.

"One important question to ask when choosing what kind of classifier to use is how much training data is currently available. In most of the cases, the trickiest part of applying a machine learning classifier in real world applications is creating or obtaining enough training data. If you have fairly little data at your disposal, and you are going to train a supervised classifier, then machine learning theory recommends classifiers with high bias, such as the Naive Bayes [37], [38]. If there is a reasonable amount of labeled data, then you are in good stand to use most kinds of classifiers [32]. For instance, you may wish to use a Support Vector Machine (SVM), a decision tree or, like in our study, a maximum entropy classifier. If a large amount of data is available, then the choice of classifier has little effect on the results and the best choice may be unclear [39]. It may be best to choose a classifier based on the scalability of training, or even runtime efficiency."

As part of this change, we also added the following citations:

1. C. D. Manning, P. Raghavan, and H. Schutze, Introduction to information retrieval. Cambridge University Press, 2008.

2. G. Forman and I. Cohen, "Learning from little: Comparison of classifiers given little training," in Proc. PKDD, 2004, pp. 161–172

3. A. Y. Ng and M. I. Jordan, "On discriminative vs. generative classifiers: A comparison of logistic regression and naive bayes." in Proc. NIPS, 2001, pp. 841–848.

4. M. Banko and E. Brill, Scaling to Very Very Large Corpora for Natural LanguageDisambiguation, 2001.

• (R2-10) Re: the number of comments needed to classify, you say something like 1400 for design and 300 for requirements. Fine. But I notice that per-project the totals you have are much lower for overall TD comments. So are you implying that with only (say) Columba, I would not get a satisfactory F1 because the number of comments is too low? Perhaps you can suggest some mitigation to that, e.g. with transfer learning. Bigger question: what leads you to think a comment that is requirement debt in project A is also requirement debt in project B? My experience is that these projects are very context specific, particularly in requirements debt.

Response:
Thank you for the comment. We believe that some words used in comments expressing technical debt are project specific and some others are more universal.

To provide more insight we highlighted in Table 3 the words that appear consistently in all top-10 lists extracted from each one of the training data sets (i.e., first two words for design debt, and first 5 words for requirement debt). We consider these words as more universal/stable features compared to the others. Although the non-highlighted features still have large weights, they can be considered as more project specific. We also added the following text in results section of RQ2:

"It should be noted that the features highlighted in bold in Table 3 appear in all top-10 lists extracted from each one of the ten training datasets, and therefore can be considered as more universal features compared to the others."

It is true we cannot support the claim that the comments from one project are enough to achieve a good accuracy. Therefore, we redesigned this experiment according to your suggestions (i.e., using a giant bag of comments from all 10 projects and incrementally adding batches of 100 comments, please refer to R2-12 for a detailed discussion of this issue)

• (R2-11) The RQ3 is really about active learning. There are in fact tools and approaches in this sub-field entirely concerned with reducing the amount of labeling needed. See https://en.wikipedia.org/wiki/Active_learning_(machine_learning)

Response:
Thank you for the comment. Indeed, it is possible that active learning could be used to reduce the amount of labeling needed. Tong and Koller in "Support Vector Machine Active Learning with Applications to Text Classification" states that in many supervised learning tasks, labeling instances to create a training dataset is time consuming and costly, and finding ways to minimize the number of labeled instances is often beneficial. Usually, the training dataset is chosen to be a random sampling of instances. However, in many cases active learning can

be employed where the learner actively chooses the training data from an unlabeled pool that will be labeled on the fly. The expected result is that this extra flexibility will reduce the learner's need for large quantities of labeled data.

However, in our case we are reporting on the performance of the maximum entropy classifier given a certain number of already labeled training data, which in the context of our study, makes sense. That said, we believe that techniques such as active learning can be analyzed and compared in future work.

To address this comment we added the following text in the Conclusions and Future Work section, paragraph 6.

"Another interesting research direction that we plan to investigate in the future is the use of other machine learning techniques, such as active learning to reduce the number of labeled data necessary to train the classifier. This technique, if proved successful, can further expand the horizon of projects that our approach can be applied to."

• (R2-12) It seems like you cannot decide whether the dataset should be one giant bag of all 10 projects, or 1 project at a time (which suggests some sort of multilevel regression, but anyway). In evaluating amount of training data needed, I don't understand why you approach this on a per-project basis. Wouldn't it make more sense to either look at the incremental improvement overall, or only on one project? There seems to be a huge assumption that these projects have similar (identical) feature distributions. That seems dangerous; perhaps not in this case, where the projects are all open source, Java projects, but certainly when we broaden the developers involved, I would expect to see a lot of drift (for example, would a German project use words like "hack"?)

Response:
Thank you for the comment. We re-designed the experiment for RQ3 using a giant bag of comments from all 10 projects and incrementally adding the comments from the training dataset in batches of 100 comments.

The approach and results part of RQ3 have been rewritten to reflect this modification. Please refer to page 10 in the revised manuscript and Figure 3.

Note: we feel that this change is too big to past in the letter, hence, we refer the reviewer to the revised manuscript.

• (R2-13) Furthermore, could you be explicit (or rephrase, if I missed it) whether the analysis changes the ordering of the projects? For example, since Ant has a lot of examples, using that first I would expect would be more useful than Columba. This is another argument for merging all the labeled features into one giant bag, and pulling them out comment by comment (or 10/100 whatever).

Response:
Thank you for the comment. Based on R2-13, we removed the project-based analysis in RQ3 and instead we add the comments in batches of 100 comments. This makes the above comment not applicable.

In case the reviewer is curious, we did not do any re-ordering the original manuscript – what we did was order the projects in descending order based on the number of comments.

• (R2-14) You don't really discuss contruct validity, which I think is key to your work. Namely, does the construct of 'self-admitted TD' match with what is actually TD? In other words, does labeling a comment TD imply that the code following is actually TD (since ultimately managers etc care about the code). You could determine this by either inspecting the code history (to show the comments are still relevant), or by running some of the code smell work against the sections of code you identified to see how much overlap there is (ideally, 100% of the fragments you identify are found by a TD code smell detector, but that won't be the case).

Response:

Thank you for the comment. Indeed, we agree with the reviewer that the original manuscript was lacking discussion on construct validity. We also agree that it is important to understand how self-admitted technical debt relates to “actual” technical debt in the source code. That said, we believe that the experiment that we conducted to address comment R2-2 also address what the reviewer is pointing out here, as we could shed some light on how self-admitted technical debt and code smells overlaps in the analyzed projects.

Also, concerning the relevancy of code comments, Fluri et al. [40] analyzed the co-evolution of source code and code comments, and found that 97% of the comment changes are consistent. In addition to that, Potdar and Shihab [14] analyzed if the developers update the source code containing self-admitted technical debt. They inspected the source code files to determine the frequency of four possible cases: Case 1 the self-admitted technical debt was removed along with change in enclosing code; Case 2 the self-admitted technical debt was removed but enclosing code was unchanged; Case 3 the self-admitted technical debt persisted despite enclosing code changing; Case 4 the self-admitted technical debt persisted with no change in enclosing code. They found that inconsistent changes (Case 2 and 3) happened between 8.8% - 27.5% of the time in one of the analyzed project.

Other aspects of the construct validity was addressed by responding to the following review comments: R1-5, R1-13, R1-14 and R2-8.

• (R2-15) I think the internal validity is otherwise ok, I appreciated you used another rater. I think my comments on other NLP approaches above also touch on improving internal validity (e.g., recall over precision).

Response:
Thank you for the comment. We believe that we addressed this comment by the changes made on comment R2-8.

== Minor
- could you report totals/avg overall in Table 1? Also percentage of TD comments might be helpful in addition to absolute #
- in S2.4, does the previous study use the same projects as this study?
- Section 3 is called "Case Study Results". This isn't a case study but rather an experiment.
- You cite the Stanford NLP tools [15], but you aren't using them (AFAIK). You are using instead the max entropy classifier at http://nlp.stanford.edu/software/classifier.html, right? That should be cited instead.

Response:
Thank you for the comment. We followed the aforementioned suggestions and made the changes in the revised manuscript.

Reviewer: 3

Public Comments (these will be made available to the author)
In this paper, the authors propose an approach to determine self-admitted technical debt (i.e., code improvements) based on comments in the source code using natural language processing techniques and machine learning. They apply their approach to 10 open source projects.

The work is very interesting, and I enjoyed reading about the methodology for identifying technical debt comments. However, I have concerns about how this work will be used and some possible threats to validity:

• (R3-1) I readily agree that technical debt is an important topic, but it's not clear how important detecting it is — what actions can be taken that could improve software quality or a software's lifecycle in some way? I would like to see the authors provide further motivation on how their approach could be used.

Response:
Thank you for the comment. To address this comment we added more motivation in the introduction. The following text that was also pointed out in R1-3 in the Introduction paragraph 6 and 7.

"The recovery of technical debt through source code comments has two main advantages over traditional approaches based on source code analysis. First, it is more lightweight compared to source code analysis, since it does not require the construction of Abstract Syntax Trees or other more advanced source code representations. For instance, some code smell detectors that also provide refactoring recommendations to resolve the detected code smells [16], [17] generate computationally expensive program representation structures, such as program dependence graphs [18], and method call graphs [19] in order to match structural code smell patterns and compute metrics. On the other hand, the source code comments can be easily and efficiently extracted from source code files using regular expressions. Second, it does not depend on arbitrary metric threshold values, which are required in all metric-based code smell detection approaches. Deriving appropriate threshold values is a challenging open problem that has attracted the attention and effort of several researchers [20], [21], [22]. As a matter of fact, the approaches based on source code analysis suffer from high false positive rates [23] (i.e., they flag a large number of source code elements as problematic, while they are not perceived as such by the developers), because they rely only on the structure of the source code to detect code smells without taking into account the developers' feedback, the project domain, and the context in which the code smells are detected.

However, relying solely on the developers' comments to recover technical debt is not adequate, because developers might be unaware of the presence of some code smells in their project, or might not be well familiar with good design and

coding practices (i.e., inadvertent debt). As a result, the detection of technical debt through source code comments can be only used as a complementary approach to existing code smell detectors based on source code analysis. We believe that self-admitted technical debt can be useful to prioritize the pay back of debt (i.e., develop a pay back plan), since the technical debt expressed in the comments written by the developers themselves is definitely more relevant to them."

• (R3-2) Did the authors do any vetting on their development set of whether or not the debt is actually present in the code when it is in the comment? In essence, are they just finding comments that *admit* technical debt, or are they actually finding locations in the code that actually *have* technical debt? For instance, did the authors consider the impact of obsolete comments? If a developer eliminated the technical debt, would the comment indicating the debt remain?

Response:
Thank you for the comment. Indeed, we agree with the reviewer that verifying the relation between the source code comment and the code itself is a must. Reviewer 2 had made a similar comment in R2-2. To address this first part of the comment we tackled the problem by conducting an experiment that we compare the overlap between our source comment based approach with a static analysis tool to detect bad smells at the file level. We added the text that report on our findings in section 4.4. Please refer to R2-2

Also for the remainder of the comment regarding the quality/consistency of the comments, we believe that we addressed this issue in comment R2-14.

That said, although remote there is still a possibility that obsolete comments could impact our results. To address this comment we added the following text into the Threats to Validity section, paragraph 4:

"On the same point, using comments to determine some self-admitted technical debt may not be fully representative since comments or code may not be updated consistently. However, previous work shows that changes in the source code are consistent to changes on comments [14], [40]. In addition, it is possible that a variety of technical debt that is not self-admitted is present in the analyzed projects. However, considering all technical debt is out of the scope of this work."

These are the citations related to this change:

1. A. Potdar and E. Shihab, "An exploratory study on self-admitted technical debt," in Proceedings of the IEEE International Conference on Software Maintenance and Evolution, 2014, pp. 91–100.

2. B. Fluri, M. Wursch, and H. Gall, "Do code and comments co-evolve? on the

relation between source code and comment changes," in Proceedings of the 14th Working Conference on Reverse Engineering, 2007, pp. 70–79.

• (R3-3) This idea is related to my first point; I can envision some scenarios where detecting admitted technical debt might be useful (such as quick statistics for software quality), and where detecting actual technical debt might be valuable (e.g., to target maintenance efforts).

There is related work to support that 97% of comment changes are consistent, which would go a long way to sidestep the obsolete comment issue. However, it is possible that the remaining 3% could in theory represent a significant sample of TD comments, given how few comments include technical debt. I would recommend the authors manually evaluate a small, representative random sample to see if this is an issue.

I believe the work in its current form identifies technical debt comments. I think the paper would benefit from a deeper discussion of the potential benefits of this information independent of knowing whether there actually *is* technical debt present.

Response:
Thank for your comment. Indeed, we agree with the reviewer suggestions. We believe that this comment has been address during the changes made while answering comments R3-1 and R3-2. As for examining the TD-related comments, our observation is that the comments vary widely, both in terms of quality and quantity, based on many factors such as the project they come from, etc. Hence, we feel it might be incomplete to only review a small sample, and at the same time doing an extensive analysis of the content to see if there exists more information in the comments warrants a study on its own. We did however make our data publicly available so that others can perform such an examination.

We hope that the provided explanation and the modified text address this issue, however, if that's not the case, we would be happy to incorporate any other changes the reviewer might suggest.

• (R3-4) My final concern is with RQ 3 in determining the necessary amount of training data. Ideally, this RQ should be answered with random samples of different sizes from all projects. Did the authors at least try every possible ordering of the projects to identify how many projects were needed to reach within 10% of the highest F1 measure? It's unclear in the text exactly what methodology was used, but the graphs in the appendix on p. 16 seem to indicate that they tried many different combinations (I just can't determine if the order of projects was random).

Response:
Thank for your comment. We agree with the reviewer that it was not clear how we ordered the projects when adding them to the training dataset. Indeed we tried out many different methodologies, but we noticed that providing more training data to the maximum entropy classifier makes it reach the performance summit

sooner. Therefore, we decided to add first projects that have more technical debt comments.

Also, we agree that to properly answer RQ3 we should consider comments from all projects and analyze the classifier performance incrementally. To address this comment (and also comment R2-12) we changed RQ3 by adding an experiment that combine all comments into one big dataset and then we incrementally increase the training dataset (100 comments at a time).

The approach and results part of RQ3 have been rewritten to reflect this modification. Please refer to page 10 in the revised manuscript and Figure 3.

• (R3-5) My issue with the conclusions the authors are making is all about the number of *comments* are needed, where in fact the only variable they are changing is the number of *projects*. Thus, I would tone down the claims in RQ3 to discuss number of projects, rather than number of comments, because it's possible that a different ordering of projects would lead to a different conclusion in terms of comments. For example, maybe training can take place on 1 large project or 2 different projects with fewer comments and reach the same results with different numbers of comments. Ideally, I would have preferred to see more data points in this section before drawing conclusions about the number of comments needed. In fact, I would suggest the authors remove the data for Comment patterns & the random classifier and instead report line graphs for the NLP-based approach only, condensed into fewer graphs (one for each kind of debt).

Response:
As explained in the previous point (R3-4), this experiment has been re-designed, and we believe that all these valid threats mentioned by the reviewer have been mitigated with the new experiment setup.

Specific comments:

• (R3-6) - Table 2: I recognize that the data set is small, but I think it would be worth reporting some statistical analysis. The relationships seem quite pronounced and might still be statistically significant.

Response:
Thank you for the comment, Indeed we agree with the reviewer that reporting statistical analysis would be interesting. To address this comment we added the following text into the original manuscript in Section 3, RQ1, paragraph 6.

"We also examine if the differences in the F1-measure values obtained by our approach and the other two baselines are statistically significant. Indeed, we find that the differences are statistically significant ($p<0.001$) for both baselines and both design and requirement self-admitted technical debt."

• (R3-7) - RQ 2: I notice that some textual features include punctuation, while others don't. Should punctuation be separated out? Is it the presence of the question mark alone in "needed?" or the word *with* the question mark that indicates technical debt? A brief justification of the author's handling of punctuation would help. Did the authors try just "?" alone in predicting technical debt? I notice a number of features include a question mark. Did the authors try technical features with & without the punctuation, or with the punctuation separated out to see the impact it would have?

Response:
Thank you for the comment. We did a lot of experimentation with the training dataset to understand which methodology would be the best fit for our approach. First, we tried to use comments as they were extracted. However, these comments were generating a lot of noise and ended up hindering the performance of the classification. We then removed the unnecessary spacing (like tabs or new lines) and also Java comment syntax characters (//, /* and */), we also had to remove punctuation such as ',' or '.' and finally we made everything lowercase as we explain in Section 2.5 of the manuscript. That said, we choose to keep interrogation and exclamation markss since they have a lot of meaning, and as we could observe during the manual classification, they can change the understanding of the comment. Also, these punctuations often helped to determine a self-admitted technical debt. To address this comment we modified the following text in the last paragraph of Section 2.5:

"In order to avoid having repeated features differing only in letter case (e.g., "Hack", "hack", "HACK"), or in preceding/succeeding punctuation characters (e.g., ",hack", "hack,"), we preprocess the training and test datasets to clean up the original comments written by the developers. More specifically, we remove the character structures that are used in the Java language syntax to indicate comments (i.e., '//' or '/*' and '*/'), the punctuation characters, and any excess whitespace characters (e.g., ' ', '\t', '\n'), and finally we convert all comments to lowercase. However, we decided not to remove exclamation and interrogation points. These specific punctuation was very useful during the identification of self-admitted technical debt comments, and provides insightful information about the meaning of the features."

• (R3-8) - section 7: I think there needs to be a new paragraph introduced on line 44 at "Then,"

Response:
Thank you for your comment. Indeed, a new paragraph on line 44 increases the readability of the manuscript. As suggested by the reviewer we added the new paragraph in Section 7.

• (R3-9) - I don't think the appendix on p. 16 is needed — I think this data can & should be integrated into two figures (one for each kind of debt), by removing the training data impact for comment patterns & the random classifier. The authors' NLP-based approach is clearly superior, so I don't think it's useful to learn about the impact of training a random classifier. To achieve just 2 graphs, the y-axis would need to be changed to using the % of the max F measure of each iteration rather than the raw F measure (or something similar that is appropriate for all the graphs on the following pages). I think this data is critically important to support RQ3, and should not be relegated to an appendix.

Response:
Thank you for the comment.
We modified the Appendix in the current version of the manuscript so that it only contains 4 tables that provide the precision and recall values for the F-measure values reported in RQ1 and Section 4.3.

We believe this information is important for the reader who is interested to learn more about the performance of the baselines, and different classifiers with respect to precision and recall. However, if the reviewer still feels that the Appendix should be modified or removed, we would be happy to address such suggestions.

Typos/grammar: please see attached pdf. The paper could use a careful reading for typos & grammar.

Response: Thank you. We did a very careful proof-reading of the paper to fix typos and grammatical mistakes.