Natural Language Processing and Program Analysis for Supporting Todo Comments as Software Evolves

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Abstract

Natural language elements (e.g., API comments, todo comments) form a substantial part of software repositories. While developers routinely use many natural language elements (e.g., todo comments) for communication, the semantic content of these elements is often neglected by software engineering techniques and tools. Additionally, as software evolves and development teams re-organize, these natural language elements are frequently forgotten, or just become outdated, imprecise and irrelevant.

We envision several techniques, which combine natural language processing and program analysis, to help developers maintain their todo comments. Specifically, we propose techniques to synthesize code from comments, make comments executable, answer questions in comments, improve comment quality, and detect dangling comments.

Introduction

Natural language elements form a substantial part of software repositories. These elements are used to communicate between users and developers (e.g., API comments, bug reports, and feature requests), and among developers (e.g., todo comments). Todo comments contain invaluable data that describe changes to code that can increase software maintenance, reliability, and quality. Despite occurring frequently in practice and containing valuable information, these elements, because of their informal nature, are largely not exploited by existing software engineering tools.

Research on combining program analysis and natural language processing (NLP), which recently started to gain some traction, is in its infancy (Ernst 2017; Arnaoudova et al. 2015; Hindle et al. 2012; Oda et al. 2015; Allamanis, Peng, and Sutton 2016; Vasilescu, Casalnuovo, and Devanbu 2017; Raychev, Vechev, and Krause 2015; Nguyen et al. 2012), and the existing work, although novel, mostly neglected comments that are used to communicate among the developers (Storey et al. 2008; Sridhara 2016).

In this position paper, we argue about the importance of content in todo comments and envision several techniques to automatically maintain and resolve those comments.

This position paper is to a large extent inspired by our extensive analysis of a large corpus of open-source projects.

Specifically, we analyzed over 30k open-source projects, which are available on GitHub, totaling 585 million lines of code (not counting comments). We found that these projects include over 297 million lines of comments (~30% of the total lines). Our analysis also uncovered more than 700k todo comments in the used corpus. We manually inspected (and discussed) hundreds of comments, code and comment changes, and commit messages. In the following subsections, we will frequently refer to this dataset and our findings related to this dataset. All examples of code and comments that we provide in this paper are taken from one of the analyzed open-source projects.

This paper mostly focuses on todo comments that contain valuable information on increasing software quality, performance, maintenance, and reliability. We consider the following three categories of todo comments. First, task comments explain what features are currently not supported or what optimizations need to be implemented (e.g., from the Google Guava project: “For optimal performance, use a binary search when targets.size() < size()/log(size())”). Second, trigger-action comments talk about changes to the code repository that would be necessary if something else is modified by developers (e.g., from Guava: “check more preconditions (as bufferSize >= chunkSize) if this is ever public”). Finally, question comments are concerned with alternative implementations, potential optimizations, and testing, which may be explored by developers only if time permits (e.g., from Guava: “Is this faster than System.arraycopy() for small arrays?”).

Regardless of the category of todo comments, as software evolves and development teams re-organize, these comments may be dangling, i.e., resolved but forgotten (Storey et al. 2008; Sridhara 2016). For example, a trigger may hold (e.g., “if this is ever public”) but the action may not be executed by developers (for very long time or ever), and developers may never have enough time to consider alternative algorithms and fine tune their existing implementations.

With the goal to help developers increase the reliability of their software, we propose several techniques to (1) synthesize code described in task comments, (2) make trigger-action comments executable, (3) answer question comments, (4) improve the quality of all todo comments, and (5) automatically detect dangling comments.
protected AbstractStreamingHasher(int chunkSize, int bufferSize) {
  // TODO(kevinb): check more preconditions (e.g. bufferSize > chunkSize)
  if (T isPublic(T.This.METHOD)) {
    checkArgument(bufferSize >= chunkSize);
    checkArgument((bufferSize % chunkSize == 0); ... } }

(a) Example from Google Guava (AbstractStreamingHasher)
public void testDynamicAttributesSupport() throws Exception { ...
  dispatcher.serviceAction(request, response, mapping);
  // TODO: remove expectedJDK15 and if() after switching to Java 1.6
  if (TRIGIT.getJavaVersion() > 5.0,
    TRIGIT.DELETE_NEXT, TRIGIT.VAR_DECL);
  String expectedJDK15 = "<input type="text"; ...;
  String expectedJDK16 = "<input type="text"; ...; ... } }

(b) Example from Apache Struts (FreemarkerResultMockedTest)

Figure 1: Examples of trigger-action comments from open-
source projects; we show how the existing comm-
ents (crossed out) can be encoded as executable statements in our
TRIGIT framework (highlighted code)

Techniques

This section describes the basic idea behind each technique
and the way we will approach the implementation.

Synthesizing Error-Reporting Code

We plan to develop lightweight synthesis techniques to gen-
erate error-reporting code for unsupported cases that are
documented by developers in the task comments (e.g., from
Guava: “support array types”). First, we will identify com-
ments that document unsupported cases. To this end, we
will explore possible supervision signals from resolved com-
ments and their corresponding code changes, crowdsourc-
ing annotation and semantic parsing of the comments. Sec-
ond, we will synthesize error-reporting code that follows
the style used in the codebase (e.g., throw an exception or re-
turn a special value from a function). Note that our goal is
not to work on full-blown program synthesis, which would
be interesting but challenging (e.g., Polikarpova, Kuraj, and
Solar-Lezama (2016)), but rather to focus on a specific do-
main of error-reporting. Basically, our goal is to make the
existing comments observable during program execution by
reporting an appropriate message for unsupported cases.

Extracting Executable Comments

We will develop techniques to help software engineers to en-
code their trigger-action comments as executable code state-
ments. This will help with repository maintenance, because
developers will not need to manually check their todo com-
m ents; instead, the executable statements will be automati-
cally triggered when appropriate.

We show several examples of trigger-action comments in
Table 1 (the top half). We found that ~10% of all todo com-
ments (in our corpus) belong to this comment category.
While it would be infeasible to support every comment writ-
ten in the trigger-action style, we plan to focus on those tasks
that update the codebase (e.g., transformations of abstract
syntax trees) when triggers are satisfied.

Our initial step is to develop a domain specific language
embedded in Java to be used to: (1) query the static features of
the codebase, e.g., required Java version, and (2) specify
code transformations, e.g., remove a method from a class.
Figure 1 shows two examples of trigger-action comments
encoded in our framework (named TRIGIT); the original
todo comments are crossed out and the statements for our
framework are highlighted.

In the first example, we use our framework to check a
modifier of the current method; if the method becomes
public, the code guarded by the trigger should become a
part of the compiled class. In the second example, we spec-
ify that a variable should be removed if the required Java
version is higher than 1.5; the required Java version can be
obtained from a build script. (Note that the statements/expr-
sions that use the variables need to be annotated too, but we
do not show this due to space limitations.) The evaluation
of the triggers will be done statically (once code is compiled),
as the queries should not depend on the dynamic behavior of
the program. Our tool, which can be implemented as a com-
piler plugin, will automatically remove the triggers and per-
form program transformations. Note that the user would still
be able to inspect/approve the changes (e.g., by executing git
diff). As the transformation engine we will use the existing
open-source platforms, e.g., Eclipse, or program transforma-
sion systems, e.g., Cordy et al. (2004). The language design
will be guided by examples, and we will evolve the language
to support cases that we encounter in the future.

Our second step is to automatically discover trigger-
action comments present in a codebase and recover the cor-
responding triggers and actions via mining explicit condi-
tion relations within the content of the todo comments; ex-
licit discourse relations can be classified with adequate ac-
curacy (Pitler et al. 2008).

In the third step, we will develop automated migration
from comments to the TRIGIT specifications, which will fol-
low our recent work on language to code for if-this-then-that
(IFTTT) recipes (Quirk, Mooney, and Galley 2015). Spec-
ically, we will train a semantic parser to map trigger-action
comments into executable code using supervision automatic-
ally extracted from the code changes made when a todo com-
ment is resolved. This supervision may be noisy, since
not all code changes may be directly related to resolving
the todo comment, but our previous work on IFTTT shows
that noisy, automatically extracted supervision from pairing
comments and code can be tolerated reasonably well.

Answering Questions From Comments

We will develop techniques to help software engineers to
make informed decisions about questions that are asked in
todo comments. In our preliminary studies, we discov-
ered that developers ask questions in todo comments more
than 10% of the time; we obtained this number by count-
ing todo comments that contain “?”. Some of these ques-
tions are shown in Table 1 (the bottom half). Many of the
questions are related to code optimization, program trans-
formation, or testing. Our plan is to focus on techniques that
will address these three types of questions. First, to answer
questions related to optimizations, we will extract suggested
code modifications from comments, apply those modifications and profile the code (by executing existing test suites) and evaluate the performance with profiles (on various machines). Second, to answer questions related to tests, we will develop techniques that extract test inputs from a question and generate new tests with those inputs; these new tests will be obtained by adjusting an automated test generation tool (e.g., Randoop (Pacheco et al. 2007)) or by extending existing (manually written) tests. Third, to answer questions related to code structure, we will extract suggested changes from Guava: “Add getters returning rowKeyToIndex and columnKeyToIndex.”), perform the changes, and measure quality of code in terms of naturalness (Hindle et al. 2012).

Our question classification system will also learn from how todo comments are answered as software evolves (e.g., files and functions that are modified and language artifacts that are added or edited); we can also learn from actions taken by developers. As some of the questions may be open-ended, we plan to develop an interactive dialog interface, which we recently used for language to code translation (Chaurasia and Mooney 2017). We plan to use dialog systems to clarify user intent and gather information—in our case, when a question is initially asked.

### Improving Todo Comments

We will develop techniques to help software engineers to write meaningful todo comments. While manually analyzing hundreds of todo comments, we found a number of comments that were hard to understand even if we read the code near those comments. We were also in disagreement about their meaning in several cases, and although we could understand a comment (e.g., from the Square Retrofit project: “TODO non-suck message”), it was clear that any technique would have a hard time to extract any useful data.

Our initial task will be to detect todo comments that are not specific enough, as well as those comments that do not follow the conventions already used in the same project. The techniques that we will develop will build on our work on text specificity (Li and Nenkova 2015) and program analysis. When we detect an unspecific comment, we will either notify a developer to provide additional clarification, highlight a part of the comment that does not follow the style (in a similar way that spellcheckers highlight typos in comments inside IDEs), or automatically reformat the comment to be consistent with other comments in the same repository. We will also provide automated comment style checkers, where the rules can be expressed by developers; this is similar to code style checkers, which are used in practice. Having specific comments that follow the same style will enable techniques from prior sections.

### Detecting Dangling Todo Comments

Prior work has shown that developers may resolve todo comments but forget to remove these comments from source code (Storey et al. 2008; Sridhara 2016); these dangling comments can waste developers’ time during program comprehension and maintenance.

We are working on a technique, based on machine learning, to automatically detect dangling todo comments. Our detection technique learns from existing software repositories. As mentioned earlier, we have already collected more than 700k todo comments. This large dataset provides examples for todo comments that were removed by developers (over 20k). We are using these examples as distant supervision signals, where we are exploring automatic labeling of examples (e.g., todo comments that are in the same file with removed todo comments). Our models are exploiting commit messages and static code analysis of changes. In the future, we plan to also utilize software histories to extract necessary context when todo comments were introduced. We will also reason about co-evolution of code and comments from when a todo comment was introduced until
it was resolved by a developer. Specifically, for each code change, we will compute its distance from todo comments, word similarity with each comment, and code structure that may be described in a comment. These sources of information provide complementary views to feature development and complementary models, so we plan to build on our prior work in co-training and ensemble models.

**Related Work**

Li et al. (2006) used text classification to validate the representativeness of their study of bug characteristics. Fluri, Wursch, and Gall (2007) empirically showed that code and comments frequently co-evolve. Padioleau, Tan, and Zhou (2009) manually studied over one thousand comments, and found that 50% of comments can be leveraged by various techniques. Haouari, Sahraoui, and Langlais (2011) introduced a taxonomy of comments and found that todo comments are the second most common type of comments. Movshovitz-Attias and Cohen (2013) used topic modeling and language models to generate comments from Java source files. Several work tackled automated generation of commit messages and mining relation from commit messages (Linares-Vásquez et al. 2015; Jiang and McMillan 2017; Andersson, Ericsson, and Wingkvist 2014; Loyola, Marrese-Taylor, and Matsuo 2017).

Tan et al. (2007) detected inconsistencies between code and comments and proposed a technique to test Javadoc comments. Zhong et al. (2011) developed a technique to infer specification from natural language API documentation and used it to detect issues in client code.

**Conclusion**

We argued that comments used to communicate among developers (todo comments) contain invaluable content that is currently neglected. We described several techniques – synthesizing code from comments, making comments executable, answering questions in comments, improving comment quality, and detecting dangling comments. These techniques, based on natural language processing and program analysis, have potential to substantially simplify software maintenance and increase software reliability.

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