Can We Use Stack Overflow as a Source of Explainable Bug-fix Data?

Henry Tang · Sarah Nadi

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Abstract  Bug-fix data sets are important for building various software engineering support tools, such as program repair or Application Programming Interface (API) misuse detection. These data sets are typically constructed from mining commit history in version-control systems. In this paper, we investigate whether Stack Overflow can be used as an additional source for bug-fix or code improvement data sets. Comments on Stack Overflow provide an effective way for developers to point out problems with existing answers, alternative solutions, or pitfalls. Given its crowd-sourced nature, answers are often updated to incorporate these suggestions. In this paper, we mine comment-edit pairs from Stack Overflow and investigate their potential usefulness for constructing the above data sets. These comment-edit pairs have the added benefit of having concrete descriptions/explanations of why the change is needed as well as potentially having less tangled changes to deal with. We first design a technique to extract related comment-edit pairs and then qualitatively and quantitatively investigate the nature of these pairs. We find that the majority of comment-edit pairs are not tangled, but find that only 27% of the studied pairs are potentially useful for the above applications. We categorize the types of mined pairs and find that the highest ratio of useful pairs come from those categorized as Correction, Flaw, and Obsolete. Our work is the first to investigate Stack Overflow comment-edit pairs and opens the door for future work in this direction. Based on our findings and observations, we provide concrete suggestions on how to potentially identify a larger set of useful comment-edit pairs, which can also be facilitated by our shared data.

H. Tang
University of Alberta
E-mail: hktang@ualberta.ca

S. Nadi
University of Alberta
E-mail: nadi@ualberta.ca
1 Introduction

Many software engineering support tools such as program repair \cite{1} or Application Programming Interface (API) misuse detection \cite{2,3} rely on bug-fix data sets, whether for building or evaluating the tools. Bug-fix data sets contain pairs of faulty/incorrect code and the corresponding fixed code. They can also include improvement changes such as using faster or more secure API calls \cite{4}. These data sets are typically constructed from linking commits from version-control systems to bug reports in issue-tracking systems \cite{5}. The commonly used linking approach relies on searching for commit messages that have specific keywords (e.g., fix) and/or explicit links to bug IDs in issue-tracking systems \cite{6,7}. While many widely used bug-fix data sets have been constructed with this approach, relying on this linkage has several limitations: not all bugs are documented in issue-tracking systems \cite{8}, not all developers are systematic about their linkage \cite{9,10}, and even worse, not every issue labeled as a bug is actually a bug \cite{11}. Additionally, since the amount of code in a version control system is typically large and tangled code changes are common \cite{12}, more advanced techniques that precisely identify the changes related to the bug are required \cite{13}. Finally, finding good explanations to attach to the identified bug or improvement such that they can be used in detection or recommender systems is difficult. On one hand, commit messages are often short, meaningless, or non-descriptive \cite{14,15} and on the other hand, bug reports are often long with too many discussions \cite{16}. Thus, the question is: are there complementary or additional sources of information that can be used to curate additional bug-fix or code improvement data sets? In this work, we investigate if Stack Overflow may be such a source.

Stack Overflow has become an essential resource for software developers. It contains a wealth of information such as code solutions, best practices, and documentation of common pitfalls in response to the asked questions. Given its crowd-sourced nature and high visibility as the go-to-place for information, Stack Overflow has the added advantage of community engagement where different developers point out various issues with the posted code snippets in the form of comments. Comments may, for example, include pointing out faster APIs, missing version information, or simply wrong answers. The answer poster, or other community members, then have a chance to edit the answer. Stack Overflow records such changes in the edit history of questions and answers, including the code snippets contained in these answers. Thus, if we can link comments to code-snipedit edits, we can provide a new data source for the applications mentioned above, such as program repair or code improvement recommendations.

Extracting these pairs from Stack Overflow potentially addresses some of the problems discussed above: Stack Overflow code snippets are typically short and targeted, which overcomes the issue of tangled changes and removing unrelated code. Additionally, comments that result in an edit likely have the description of the issue that was addressed, which means that these comments can provide meaningful explanations that can accompany any code-
change recommender tools. For example, answer [52517618] contains code that converts a byte array to a string as follows:

```java
String s = new String(bytes, 'UTF-8');
```

This code snippet then gets updated to

```java
String s = new String(bytes, StandardCharsets.UTF_8);
```

based on the following comment: “On Java 7 you can also use new String(bytes, StandardCharsets.UTF_8); which avoids having to catch the UnsupportedEncodingException”. Thus, a tool that detects that a developer wrote the former (pre-edit) piece of code could suggest the latter (post-edit) piece of code and accompany that suggestion with the comment to explain why the suggestion is being made.

To explore the feasibility of using Stack Overflow as a source for bug-fix or code improvement data, we first need to design a technique that maps comments to their corresponding edits. In other words, we need to extract comment-edit pairs, i.e., a comment and the resulting edit that addressed this comment. To do so, we leverage the SOTorrent [17] dataset and adapt and improve a previous matching approach we designed to identify ignored comments [18]. At a high level, our automated approach matches a comment to an edit if the comment occurred before the edit and the comment mentions a code term that gets added to or removed from a code snippet in the edit.

To support our investigation of using these comment-edit pairs for creating bug-fix/code improvement data sets, this paper then answers the following research questions:

- **RQ1** What is the precision of an automated technique for extracting comment-edit pairs from Stack Overflow? There is currently no way on Stack Overflow to relate a comment to an edit so the first step of this research is to establish an automated technique for doing this pairing, and to evaluate its precision.

- **RQ2** How tangled are the changes in Stack Overflow comment-edit pairs? To investigate if the identified comment-edit pairs do indeed overcome the challenge of tangled changes, we investigate how often do the changes in mined pairs address issues other than that pointed out in the related comment.

- **RQ3** What type of changes occur in Stack Overflow comment-edit pairs? To understand what potential types of datasets and related software engineering applications can these comment-edit pairs be used for, we need to understand the types of changes that occur in them (e.g., syntax error fixes vs. catering the solution to the original poster’s question).

- **RQ4** What is the potential usefulness of the extracted comment-edit pairs for curating bug-fix/code improvement datasets? Not all the mined comment-edit pairs are necessarily useful for bug-fix/code-improvement data sets. Thus, it is important to understand how many of the comment-edit pairs are useful for the intended applications. We consider a comment-edit pair as useful for code recommender systems if (1) the edit addressing the comment happens to an existing code snippet in the answer such that there is code to be matched in a target system and (2) if the comment describes this change in a way that is understandable in isolation of the
posed Stack Overflow question. We also investigate how tangled these useful pairs are, and which categories they fall under. To further demonstrate usefulness, we also submit 15 pull requests based on our mined pairs to 15 different open-source repositories.

To answer the above research questions, we run our automated matching technique on 5 popular Stack Overflow tags. We then manually analyze a statistically representative sample of 1,910 detected comment-edit pairs to confirm true matches. We record the type of suggestion and change being made, the presence of tangled changes in the edit, and the usefulness of the pair for the 1,482 confirmed pairs we find.

Our results show that the precision of our automated approach is 74%-80% across the five tags and that only 11% of the 1,482 confirmed pairs are tangled while 27% are useful. To categorize the confirmed pairs, we use a coding guideline from previous work [19] that analyzed the types of comments on Stack Overflow, without looking at corresponding edits. We find that 34%, 16%, and 13% of the confirmed pairs are of types Error, Request, and Correction respectively, collectively consisting over 50% of the confirmed pairs. However, when looking specifically at useful pairs, we find that types Correction, Obsolete, and Flaw are the most useful. This is promising for future applications as these types of comments are relatively more general and the corresponding edits will be applicable in a general setting. Additionally, 9 out of the 15 pull requests we submitted based on our collected data have already been accepted.

To the best of our knowledge, this is the first work that maps Stack Overflow comments to edits and studies the potential of using these comment-edit pairs for constructing bug-fix/improvement data sets that also provide explanations for the provided changes. The summary of our contributions in this paper are as follows.

- We implement an automated approach for matching comments to edits. We apply this to 5 popular Stack Overflow tags (Java, JavaScript, Android, Python, and PHP) and extract a total of 248,399 comment-edit pairs.
- We manually analyze 799 comments from 100 answers (20 from each of the five tags) to create a ground truth of 88 comment-edit pairs, and use it to evaluate our matching approach and compare it to a naive baseline.
- We manually analyze a statistically representative random sample of 1,910 comment-edit pairs and confirm true matches for 1,482 pairs. We record the category the comment belongs to, the presence of tangled changes, as well as its usefulness for bug-fix/improvement data sets.
- Based on the above collected data, we answer four research questions to determine if comment-edit pairs can be used in future software engineering applications. We also discuss challenges and opportunities for future work in this direction.
- For additional external validation, we use the confirmed comment-edit pairs to submit 15 pull requests to different open-source GitHub repositories. To date, nine of these pull requests have been accepted.

All our code and data are publicly shared on our artifact page [20].
2 Related Work

Data from Stack Overflow has been used extensively in previous work with varying purposes. While some papers focus specifically on studying various characteristics of Stack Overflow and how information evolves on it \cite{21,22,23}, others use information from Stack Overflow for specific purposes such as augmenting documentation, code search, or improving code analysis tools \cite{24,25,26,27,28,29}. Given the nature of our work, which establishes a relationship between comments and code edits on Stack Overflow and investigates the nature of these pairs, in this section, we focus only on related work that studied/used comments or edits on Stack Overflow (SO).

Related work we rely on. Our recent MSR challenge paper \cite{18} quantified how often comments cause answer updates, and how often comments are ignored even when they should have resulted in an answer update. We used three heuristics for matching comments to edits and categorizing them: (1) code checks where a comment caused an update if a code element in the comment is added or removed in the edit, (2) keyword phrase checks that suggest that the comment is explicitly asking for an edit but no edit occurred, and (3) question checks where a comment explicitly asks a question about the posted code. Our results showed that code checks resulted in the most matches between comments and edits and that most of the wrongly labeled pairs occurred when we tried to deduce that a comment should warrant an update and was ignored, or that a comment does not warrant an update. Based on these findings, in this paper, we only use the code check heuristic and focus on finding comment-edit pairs where an update actually occurred. This current paper differs from our previous work in terms of goals: we do not try to automatically categorize all comments and do not look for ignored comments. Our goal is to find comments that actually caused an edit, and to study the comment-edit pairs in terms of their suitability for creating bug-fix/code improvement data sets. Additionally, we improve the matching algorithm and evaluate it against a manually constructed ground truth. We also manually validate a statistically representative sample of the pairs our tooling detects, measure the precision, and publicly share these confirmed pairs.

Another recent work we rely on is that by Zhang et al. \cite{19}. In that work, the authors analyzed comments on Stack Overflow. They investigated the information discussed in comments and perform open coding to categorize the analyzed comments. They defined 7 broad categories and 17 sub-categories of comments. They did not, however, attempt to match comments to edits or analyze the code changes in edits. Given that the comments we find in comment-edit pairs are a subset of all comments on Stack Overflow, we use the categories they create as our coding guideline for categorizing comments. In other words, given their categories, we perform closed-coding (i.e., when codes/labels are predetermined) to categorize our comment-edit pairs. Some of the categories of comments they find, such as pointing out errors or weaknesses in answers or providing alternative solutions, give us assurance that
finding the edits corresponding to these comments can potentially be useful for bug-fix/code-improvement data sets.

**SO for Syntax Errors.** Wong et al. [30] studied edits to Python code snippets on Stack Overflow in order to produce a syntax error dataset. Their goal was to make a free, open, and public data set that would be representative of the kinds of syntax errors general developers would have. At a high level, they parse the before and after versions of the most recent edit in an answer. If the prior version included a parse error and the most recent did not, then they store the two versions as a syntax error and fix respectively. Our work differs as we focus on linking comments and edits to attach a reason for an edit. We also consider all types of fixes or improvements and do not focus solely on syntax errors.

Thiselton et al. [31] used Stack Overflow answers in order to provide better compiler error messages for active development. Their work takes a Python compiler error message and constructs a Stack Overflow query. They take the first question on the first page that is returned by the query that contains at least one answer. They then take the accepted answer (or highest voted answer if there is no accepted answer) and modify the compiler error to incorporate a summary of the answer they found. They do not use comments or edits on a Stack Overflow answer at all. However, their work highlights that novel applications using information from Stack Overflow can be useful in helping developers during active development.

**Collaboration Characteristics on SO.** Adaji et al. [32] also studied edits and comments on Stack Overflow. Unlike our work that analyzes the contents of comments and edits to link them together, their work used comments and edits to study collaboration characteristics on Stack Overflow with the goal of finding the types of users that contribute to high quality answers. Specifically, they investigated whether the number of comments on an answer or the reputation of the editor are correlated with the answer quality. Their results showed that most of the edits made were by users with no badges and that most high quality answers had more comments rather than less. Based on these findings, we study all comments and edits, regardless of the reputation of the user or the score of the answer.

Wang et al. [33] studied Stack Overflow badges that are related to revisions of answers. They found that most revisions were made in spikes (i.e., many revisions made on the same day) rather than spread out over different days. These spikes in revisions coincided with the days Stack Overflow were awarding badges to members and that these revisions were mostly simple revisions (i.e., typo correction and formatting). They also noted that most of the revisions made on these days needed to be rolled back due to the revision being incorrect or undesired. They concluded that the current system of using badges was insufficient in enforcing answer quality and that there needed to be a change in how Stack Overflow encourages revisions without lowering the quality of
Can We Use Stack Overflow as a Source of Explainable Bug-fix Data? 7

answers. Our work focuses on the contents of the revisions and relating them to comments, as opposed to motivation schemes for performing the edits.

Answer Quality. Dalip et al. [34] created a learn to rank approach with the goal of automatically estimating the feedback a user would give regarding the quality of an answer. To do so, they extracted features related to both comments and edits. All their features are quantitative (e.g., number of edits, number of comments, or number of users who commented on answer), and they did not analyze the content of the comments or map comments to edits.

Diamantopoulos et al. [35] analyzed answer edits to determine what makes an optimal answer. With that information, they discuss future Stack Overflow tools that could suggest edits on an answer to improve its quality. While our work can help with similar future goals, the methodology and the focus of both studies differ substantially. Diamantopoulos et al. [35] used a neural network to study the edits made on Java answers and applied clustering to extract related edits. They then used the “commit” message associated with an edit to come up with representative descriptions for each cluster; however, as they also point out, having a message associated with the edit is rare. Since comments on an answer are much more common and are also more descriptive, we believe that studying answer comments to understand the types of edits that occur may provide more explanations and intuitions for answer edits, which would make any follow up recommender system more useful to users. Additionally, we pair comments with the corresponding edits while they do not.

Clarification Comments. Rao et al. [36] used a neural network to learn different kinds of clarification questions that were asked in the question comments to improve the question, e.g., What version of X are you using? While they do perform some matching of the comments posted on a question to the question edits, they focused only on explicit question statements found in comments (i.e., a sentence that ends with a question mark). They also did not compare the content of the comment to that of the edit, and assume that the first edit after a question is posted in a comment is the response to that question. Along similar lines, Jin et al. [37] studied how edits to a question affect the answers the question receives. They focused on the edits made to a question before and after it received an accepted answer and how these edits affect the quality of received answers. In contrast to both efforts, we try to match code terms in a comment and an edit, and we focus on answer edits rather than question edits.

Summary. To summarize, apart from various technical/methodological differences noted above, the most important differences to prior work is (1) the motivation of our work for constructing data sets that have before/after code versions with associated explanations, (2) that we analyze the contents of comments and edits to match them, (3) that we extract pairs of comments and

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1 note that they refer to this message as comment in their paper, but it is not a comment on the answer, but rather the message the editor provides with their edit
their corresponding edits, and (4) that we study various characteristics, such as tangledness and usefulness, of these comment-edit pairs.

3 Mapping Comments to Edits

In this section, we describe our methodology for matching comments to edits. Our goal is to extract comment-edit pairs \((c_i, e_j)\), where comment \(c_i\) caused edit \(e_j\) to occur.

As our main data source, we use the SOTorrent dataset [17] which captures the edit history of all Stack Overflow posts (we use version 2019-09-23). In SOTorrent, a Stack Overflow post is split into text and code blocks, based on the html formatting used in the post. Text blocks mark any text in the post, including inline code, while code blocks mark explicit code blocks formatted using the `<code>` html tag or the markdown back-tick symbol. An edit to a given post is thus any change to one or more of its text or code blocks. Given the goal of our work, we focus on edits to code snippets in Stack Overflow answers. We analyze all answer edits from five popular tags on Stack Overflow: Java, Javascript, Php, Python, and Android. These five tags contain a total of 11,119,517 answers, 12,130,068 comments, and 4,322,506 edits.

3.1 Ground Truth Creation

As a first step, we create a ground truth that can help us evaluate and refine any automated matching technique we develop. To select the answers that we will include in our ground truth, we used stratified sampling to select 20 answers from each tag. Our stratification strategy was to select two answers in each of the following categories: high (above 1000) score, low (below zero) score, recent creation date (after Jan 01, 2018), and old creation date (before Jan 01, 2009). This resulted in 8 selected answers. Additionally, we randomly select 2 answers that match each possible combination of a large number (greater than ten) and small number (less than ten) of edits and comments, e.g., an answer with greater than ten edits but only two comments. This results in an additional 8 answers. Finally, we select four additional random answers with at least one edit and one comment to create our 20 answers for each tag. In total, our ground truth contains 100 answers with a total of 521 edits and 799 comments.

The two authors then separately evaluate all 100 answers. For each comment in the answer, they separately analyze the edits for each answer to determine if the comment caused an edit using the following criteria:

1. The edit occurred after the comment.
2. The topic of the comment is related to the update in the edit.

We used only the above criteria to mark a comment as having caused an edit; it did not matter if the edit affected a text block or a code block or if the
Can We Use Stack Overflow as a Source of Explainable Bug-fix Data?

Table 1: Ground Truth Statistics

| Tag   | Answers | Edits | Comments | Median comments | Median edits | Comment-edit pairs |
|-------|---------|-------|----------|-----------------|-------------|-------------------|
| Java  | 20      | 95    | 148      | 5.5             | 2.0         | 20                |
| Javascript | 20 | 105    | 158      | 6.0             | 3.0         | 14                |
| Android | 20    | 101   | 202      | 8.5             | 3.0         | 25                |
| Python | 20      | 103   | 136      | 5.5             | 3.0         | 13                |
| Php   | 20      | 117   | 155      | 6.0             | 3.0         | 16                |
| Total | 100     | 521   | 799      | -               | -           | 88                |

A comment contained any code. This was intentional to avoid any bias towards our heuristics of using code terms for matching comments to edits, which we describe later in Section 3.2. For example, in answer 281433, we would match the comment “But he is not calculating a simple mean. Remember there were only three votes given in his example.” to the edit that removed the SQL query that implemented a simple mean, even though there are no explicit code terms used in the comment. The two authors then discussed and resolved any disagreements. Overall, our Cohen’s Kappa score [38] for matching comment-edit pairs was 0.71.

Table 1 shows the descriptive statistics per tag in our ground truth. In total, we analyzed 100 answers with 799 comments and 521 edits to construct a ground truth of 88 comment-edit pairs.

3.2 Automatically Matching Comments and Edits

Algorithm Overview. Given our motivation that mined comment-edit pairs can be later used for creating bug-fix/code improvement data sets for use in various recommender systems, we only consider edits to code snippets. Based on that, the high-level idea of the algorithm is that if a comment mentions a code term that then gets removed or added in a later code edit, we can reasonably assume that the comment caused that edit.

Data Preparation. As a first step, we create two tables that are necessary to store the post-processed SOTorrent data that is relevant for our analysis. The first table we construct is adapted from the EditHistory table based on a blog post from Baltes [39], one of the authors of the SOTorrent dataset. This table keeps track of questions, answers, comments, and edits to both the questions and answers. This table also provides the creation date for each of these events and allows us to order the edits and comments in chronological order. We include the parent post id in this table to allow us to find all the answers, edits, and comments related to a specific question. The second table we create is called EditHistory_Code, which is built from the EditHistory table and is similar except that instead of containing all changes in the edits, it contains
```python
1 matched_pairs = ∅
2 for a_i in all_answers:
3   for c_j in comments(a_i):
4     comment_code_terms = extractCodeTerms(c_j)
5     prev_edit = e_i
6     for e_k in edits(a_i):
7       if date(e_k) > date(c_j):
8         prev_edit_code_terms = extractCodeTerms(prev_edit)
9         edit_code_terms = extractCodeTerms(e_k)
10        edit_code_diff = edit_code_terms △ prev_edit_code_terms
11        code_matches = edit_code_diff ∩ comment_code_terms
12        if code_matches:
13           matched_pairs = matched_pairs ∪ (c_j, e_k)
14           break
15     prev_edit = e_k
```

Listing 1: Algorithm for matching comments to edits

only answers with code blocks and the corresponding edited text from only code edits. We obtain the actual code edits from the PostBlockVersion table provided in the SOTorrent dataset [17]. The EditHistory_Code table we construct contains all the initial body of an answer, its subsequent edits, and comments to the answer in chronological order, while removing all unnecessary data such as the title version history and textual answers and edits. Our program needs both the EditHistory and EditHistory_Code tables to analyze whether comments cause edits to answers.

**Algorithm Details.** Listing 1 shows the algorithm we use to match comments to edits. We use the example in Figure 1 as a running example to explain the algorithm. For each answer in the data set (Line 2), the program iterates through all the comments in chronological order (Line 3). It then extracts all code terms found in a comment, storing them in `comment_code_terms` (Line 4). Figure 1 shows the extracted comment code terms on the left side of the figure. To extract code terms, we first look for explicit markdown or html tags (i.e., `<code>`) Since not all users strictly follow the formatting guidelines, we also use a series of regular expression patterns to detect code terms that have not been explicitly formatted. We start with the list of regular expressions used by Treude et al. [40]. We modify some of the expressions based on testing them on the ground truth set and also remove unnecessary or problematic expressions. Since the original set of expressions was developed mainly for Java, we also added additional regular expressions catered to the other languages in our dataset. The full list of regular expressions we use can be found in our artifact page [20].

The algorithm then iterates over all edits for this answer, in chronological order, to try to match them to the current comment (Line 6). When the program finds an edit that was made after the comment (Line 7), it extracts the code terms found in the current edit (which has the snapshot of the code after
In your example you have “yourClientObject” and then two lines down you have “yourClient” is there a difference? I wanted to make sure I wasn’t missing something there. -user1161447 Jan 23 '12 at 20:35

Fig. 1: Example from SO answer 8949391 showing the matching process between comments and edits, based on code terms. The comment shown is matched to edit e5. Example has been reproduced and edited for better visualization. Note that the *2 notation shows cardinality of how many times that code term exists.

the change) and the previous edit (which has the snapshot of the code before the change), using the same code identification technique used for comments (Lines 8-9). The program then takes the set difference between these two sets of code terms to determine any added or removed code terms (Line 10). In Figure 1, the symmetric difference of the edits is displayed on the right side of the figure. Finally, it compares the code terms found in the comment to the code terms found in the difference between the two edits (Line 11). Since the code term used in the comment may not be exactly the same as that used in the code due to typos or placeholder text in the code snippet, we calculate the Levenshtein distance [41], using the fuzzywuzzy library in Python [42], between the code terms in the comments and those in the edits to determine a match. We consider two code terms as a match if their similarity ratio is above 90%. If there is a match, it labels the comment as having resulted in an edit, and adds this comment-edit pair to the set of matched pairs (Lines 12-14).
Table 2: Matching Evaluation on Ground Truth Data Set

| Tag     | Existing Pairs | Our Matching Program | Proximity Based Baseline |
|---------|----------------|----------------------|--------------------------|
|         | Detected | Recall | Precision | Detected | Recall | Precision |
| Java    | 38       | 20     | 47%       | 81       | 64%    | 28%       |
| Javascript | 33      | 14     | 30%       | 65       | 70%    | 35%       |
| Android | 40       | 25     | 36%       | 96       | 69%    | 28%       |
| Python  | 38       | 13     | 23%       | 59       | 53%    | 34%       |
| Php     | 45       | 16     | 24%       | 63       | 51%    | 37%       |
| Overall | 194      | 88     | 32%       | 364      | 60%    | 32%       |

In Figure 1, the matched code terms (yourClient and yourClientObject) are shown at the bottom of the figure. Since there are matched code terms between the comment and the edit, in this example, we would say that the given comment is matched with e5. Note that the break on Line 14 indicates that a comment is matched to the first edit it is related to.

3.3 Comparison with Ground Truth

Before running our automated matching strategy on all the data we have for all tags, we want to evaluate its effectiveness and fix any issues. Thus, we run the above matching algorithm on the manually created ground truth set of 100 answers from Section 3.1 and calculate recall and precision. Recall is the percentage of comment-edit pairs the program could detect from the manually confirmed pairs in the ground truth, while precision is the percentage of comment-edit pairs identified by the program that were correct. Additionally, to understand if the code matching algorithm we use brings in any value, we compare our results to those of a simple baseline. This baseline simply matches a comment to the chronologically nearest edit that comes after it, regardless of the content of the comment or edit. We show the results in Table 2.

As shown, the recall is low but the precision is relatively good (ranging from 56% - 85% and 70% overall. To understand when our matching fails, we manually analyze the false positives and false negatives. The main cause of a low recall (i.e., false negatives) is that there were comments in the ground truth that caused an edit but did not contain any code suggestions. Our program is only able to pair comments and edits that share a code pattern, as such it was not able to find these comment-edit pairs. While this is expected and it would have been more “fair” to evaluate our program on the comment-edit pairs it could potentially capture (i.e., those with code), we chose to conduct a strict evaluation to understand the worst case performance of the algorithm in terms of how many pairs it could potentially capture. On the other hand, the majority of false positives occur, because of coincidental matches in the comment and an edit i.e., the program finds a code suggestion using the regular expressions that was both in the comment and in an edit, but the edit was
Table 3: Number of answers, edits, and comments in each of the five Stack Overflow tags, as well as the number of comment-edit pairs we detect for each tag

| Language | Answers   | Edits     | Comments  | Detected comment-edit pairs |
|----------|-----------|-----------|-----------|-----------------------------|
| Java     | 2,586,447 | 895,737   | 2,321,296 | 51,358                      |
| Javascript| 2,924,662 | 1,281,433 | 3,571,622 | 65,373                      |
| Android  | 1,722,580 | 490,565   | 1,668,634 | 34,596                      |
| Python   | 1,785,914 | 903,159   | 2,060,513 | 44,551                      |
| Php      | 2,099,914 | 751,612   | 2,508,003 | 52,521                      |

not caused by that comment. For example, a comment asks for clarification on function \texttt{myFunction(...)}. The program finds this code term and adds it to \texttt{comment\_code\_terms}. After this comment was made, an edit was made that cleaned the answer, but did not answer the clarification inquiry, e.g., it removed debug statements or fixed indentation. Our program catches the change that included \texttt{myFunction(...) and adds it to edit\_code\_terms}, resulting in matching the comment to the edit even though they are not related.

For the purposes of using the extracted pairs to build data sets, we are more concerned with precision than recall. When compared to the proximity based baseline, our program achieves a much higher overall precision (70% vs. 32%), which gives us confidence in using our matching algorithm to answer our five research questions.

4 RQ1: Precision of Comment-Edit Pairs

We now discuss RQ1, which focuses on the precision of our automated mapping strategy. While the ground truth evaluation gave us confidence to proceed, our ground truth is still limited in size. Thus, for RQ1, we run our matching program on the data from all five tags. We first describe our methodology and then report the results.

Methodology. We first run our matching program on the data from all five tags we focus on. Table 3 shows the descriptive statistics for this data, as well as the number of comment-edit pairs detected by our tool.

Calculating precision requires manually analyzing the detected pairs. Since it is not feasible to manually validate close to 250,000 pairs, we take a statistically representative sample for each tag. For a confidence level of 95% with a 5% confidence interval, we need a sample size of 382 pairs for each tag. Therefore, we randomly select 382 pairs from each tag for our manual validation, resulting in a total of 1,910 comment-edit pairs to be validated.

The two authors of the paper then separately analyzed all 1,910 comment-edit pairs, with the goal of confirming whether the identified comment is re-
Table 4: Precision of Detected Comment-edit Pairs Across the Full Data Set

| Tag       | Pairs Analyzed | Pairs Confirmed | Cohen’s Kappa | Precision |
|-----------|----------------|-----------------|---------------|-----------|
| Java      | 382            | 305             | 0.67          | 80%       |
| Javascript| 382            | 307             | 0.77          | 80%       |
| Android   | 382            | 284             | 0.86          | 74%       |
| Python    | 382            | 292             | 0.75          | 76%       |
| Php       | 382            | 294             | 0.77          | 77%       |
| Total     | 1,910          | 1,482           | 0.77          | 78%       |

lated to the corresponding edit in the pair. Thus, each comment-edit pair was labeled with either 0 (comment is not related to the edit) or 1 (comment is related to the edit). After the separate labeling process, both authors discussed any disagreements and resolved conflicts. We use Cohen’s Kappa score [43] to calculate the inter-rater agreement rate.

Results. Table 4 shows the precision of our matching strategy, as well as Cohen’s Kappa, for each analyzed Stack Overflow tag. The last row of the table shows the overall aggregate results over all analyzed data.

As shown, our Kappa score ranged 0.67-0.86 across the five tags. Out of the 1,910 pairs we analyze, we confirm 1,482 pairs. The precision per tag ranges from 74-80%. When considering all 1,910 pairs, the overall precision of our algorithm is 78%. We also note that the precision across the five tags is fairly similar, which suggests that our matching heuristics are not biased toward a particular programming language or lexicographical pattern.

RQ1: Across the five tags, the precision of our automated comment-edit mapping algorithm is 78%.

5 RQ2: Tangled Changes

In the introduction, we speculated that one of the attractive qualities of using Stack Overflow edits is that changes on Stack Overflow are likely to be less tangled than those found in commits in version-control systems. In this research question, we investigate if this is true in practice.

Methodology. For each of the 1,482 confirmed comment-edit pairs found in RQ1, we also record whether the edit contains tangled changes or not. An edit contains tangled changes if the edited answer contains additional changes that are not related to the matched comment. An example of a tangled change would be an edit that addresses multiple comments at a time. This usually occurs when the answer poster does not look at their answer for a period of time while other users view the answer and make comments on what, if any, changes they recommend. The answer poster then returns and decides
Table 5: Number of useful pairs and tangled edits in the confirmed comment-edit pairs

| Tag   | Confirmed Pairs | Tangled          | Useful          |
|-------|-----------------|------------------|-----------------|
|       | Kappa Score     | Count (%)        | Kappa Score     | Count (%)        |
| Java  | 305             | 0.79             | 41 (13%)        | 0.79             | 67 (22%)        |
| Javascript | 307           | 0.65             | 41 (13%)        | 0.70             | 91 (30%)        |
| Android| 284             | 0.59             | 23 (8%)         | 0.81             | 71 (25%)        |
| Python | 292             | 0.61             | 29 (10%)        | 0.78             | 107 (37%)       |
| Php   | 294             | 0.64             | 27 (9%)         | 0.62             | 60 (20%)        |
| Overall| 1,482           | 0.67             | 163 (11%)       | 0.74             | 396 (27%)       |

Results. Table 5 shows the number of tangled pairs, both per tag and overall. As shown, only 11% of the total confirmed pairs are tangled. These results coincide with our intuition that since Stack Overflow snippets and answers are typically short, their edits would mostly focus on one issue at a time. From our general observations, the main reason for tangled changes are when the answer poster includes additional refactorings to make the answer more concise or readable while addressing the feedback in the comment.

RQ4: Our results confirm our intuition that the code changes in Stack Overflow comment-edit pairs are rarely tangled. Specifically, only 11% of the 1,482 confirmed comment-edit pairs we analyzed contain tangled changes.

6 RQ3: Types of Changes in Comment-Edit Pairs

In RQ3, we look at the types of changes that occur in comment-edit pairs. Understanding the types of changes helps in determining what software engineering applications and recommender systems can this data be used for.

Methodology. As mentioned in Section 2, Zhang et al. [19] previously categorized the type of comments that exist on Stack Overflow. Through open-coding, they derived 7 high-level comment types (e.g., improvement, inquiry, praise) and 17 subtypes (e.g., support, flaw, reference). Thus, for consistency, we opt for not re-inventing the wheel by performing open coding and developing new categories ourselves; instead, we reuse their fine-grained subtypes to label our data. Given that their types cover all comments on Stack Overflow, the pairs we extract naturally fall under a subset of these types. This also means that some of the types they have do not make sense in our context.

to create one edit to address all the comments received. Similarly, a tangled edit includes addressing a comment but also making cosmetic changes, such as variable renames in the code snippet or text reformulation in the answer. Again, the two authors independently labeled tangled changes and discussed disagreements.

RQ4: Our results confirm our intuition that the code changes in Stack Overflow comment-edit pairs are rarely tangled. Specifically, only 11% of the 1,482 confirmed comment-edit pairs we analyzed contain tangled changes.

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Table 6: Categories used from Zhang et al. [19] to label confirmed comment-edit pairs

| Category   | Description                                                                 | Example comment                                                                 |
|------------|------------------------------------------------------------------------------|---------------------------------------------------------------------------------|
| Correction | Provides code correction to the answer                                        | 16994146: This gives an undefined variable error. To fix it, change `var_dump($thing);` to `var_dump($thing);` |
| Extension  | Extends the answer to other cases by making the code more generic, catching corner cases, etc. | 514517: One more thing: if you want the range to be inclusive, do `for` in code in range(ord('a'), ord('z')+1): print unichr(code) |
| Flaw       | Points out flaws or limitations. Comments that make small changes but do not change the logic also fall here. e.g., replacing a `for` loop with a `forEach` loop | 2061144: Don’t use `query.getSingleResult()` as an exception could be thrown if there is not exactly one row returned - see http://java.sun.com/javee/5/docs/api/javax/persistence/Query.html#executeQuery() |
| Error      | Points out errors in the code. i.e., incorrect logic resulting in an error or exception | 390379: I tried but it gives error java.lang.IllegalStateException: You need to use `Theme.AppCompat` on `setContentView(R.layout.activity home screen);` |
| Obsolete   | Points out obsolete APIs, libraries etc.                                     | 24964658: While this answer works and seems correct, it was written in 2014 and is now outdated. From Angular 1.4 there is a built in way to do it by using `$httpParamSerializer`. Check the answers below for an explanation and an example. |
| Disagree   | Disagrees with the answer by clarifying the needed requirements. i.e., the answer does not actually answer the question | 40813524: But I really need to set the variable at `componentDidMount()` because it’s an object that depends on DOM elements |
| Question   | Asks clarification question about the answer                                 | 15976303: So then `knownWordsArrayList = new ArrayList<String>(h);` leaves me with all the new words? |
| Request    | Requests information that is outside the initial question. e.g., follow up questions or asking for an example | 40611808: `path_image` is a string value. How to set that string value to `setBackgroundResource()` |
| Solution   | Provides alternative solutions to the answer                                | 55069962: You could even do something like `td:is([data-test="specific-location"],[data-test="specific-location1"]);` to get something a little more compact. |

For example, a comment praising or supporting the answer will not likely end up causing an edit. In Table 6, we show the subset of 9 subtypes (referred to as category) that are applicable to our context. For clarity, we also add
Table 7: Number of total and useful pairs per category

| Category | Java All | JavaScript All | Android All | Python All | Php All | Overall All |
|----------|----------|----------------|-------------|------------|---------|-------------|
|          | Useful   | Useful         | Useful      | Useful     | Useful  | Useful      |
| Correction | 23 (93%) | 47 (34%)       | 26 (17%)    | 52 (43%)   | 51 (30%)| 199 (158%) |
| Extension | 3 (100%) | 13 (40%)       | 2 (66%)     | 2 (100%)   | 3 (60%) | 11 (30%)   |
| Flow      | 22 (65%) | 21 (74%)       | 5 (60%)     | 20 (62%)   | 18 (78%)| 79 (25%)   |
| Error     | 98 (32%) | 126 (41%)      | 88 (40%)    | 108 (34%)  | 101 (34%)| 511 (27%)  |
| Obsolete  | 1 (100%) | 2 (50%)        | 3 (100%)    | 1 (100%)   | 9 (60%) | 10 (67%)   |
| Diagnosis | 39 (22%) | 31 (17%)       | 0 (0%)      | 0 (0%)     | 0 (0%) | 104 (6%)   |
| Question  | 35 (11%) | 28 (11%)       | 21 (14%)    | 24 (14%)   | 143 (6%)| 143 (11%)  |
| Request   | 60 (1%)  | 44 (1%)        | 34 (0%)     | 45 (0%)    | 236 (3%)| 236 (1%)   |
| Solution  | 22 (50%) | 8 (21%)        | 0 (0%)      | 0 (0%)     | 0 (0%) | 0 (0%)     |
| Other     | 2 (0%)   | 3 (0%)         | 8 (0%)      | 1 (0%)     | 7 (0%) | 21 (0%)    |
| Total     | 305 (22%)| 307 (21%)      | 284 (20%)   | 292 (20%)  | 294 (20%)| 1482 (27%) |

an example of a real comment from a comment-edit pair that matches this category, as well as any additional assumptions we made about the category in our coding guidelines which may have not have been clear in the original publication. Given these categories, we perform closed coding where the two authors independently label each confirmed comment-edit pair and then discussed disagreements. Our inter-rater agreement for this task ranged from 0.82 - 0.95 and was 0.88 overall.

Results Table 7 shows the number of comment-edit pairs in each category, per tag. For now, we focus on the All column which shows the categories across all confirmed pairs in each tag (and overall in the last column). From the overall numbers (which are also consistent with the individual tag numbers), the most frequent type of comment-edit pairs is the Error category, followed by Request, and Correction. This is good news since the pairs of type Error and Correction could potentially be used for automated bug-fix recommendations or applications.

It is interesting to see that pairs of type Question (143 total pairs) are also frequent. As shown in the example in Table 6, a comment of category Question asks clarifications about the already posted solution, such as asking what a specific statement is doing or why is there a need to call a specified method call. The edit usually improves the code snippet to answer that question and/or provides additional textual explanation.

The number of pairs of type Extension and Obsolete are low. This is consistent with Zhang et al.’s findings where they find that only 0.8% of the comments they analyze are of type extension and 1.0% are of type obsolete [19].

RQ3: The most common categories for the extracted comment-edit pairs are Error, followed by Request, and Correction.
7 RQ4: Usefulness of Comment-Edit Pairs

So far, we have shown that the precision of the extracted pairs is high (i.e., the comment is really related to the edit), the majority of the edits are not tangled, and that the types of comments and changes are promising for various software engineering applications. However, it is still not clear if these pairs are actually *useful* in the end. This is what we investigate in this last research question.

**Methodology.** As part of our labeling, we also record the usefulness of the 1,482 confirmed pairs. As mentioned in the introduction, we consider a pair as *useful* if (1) the edit happens to an existing code snippet in the answer and (2) if the comment describes this change in a way that is understandable outside of the posed Stack Overflow question. The first criterion stems from how these bug-fix/code improvement data sets are typically used. For example, the before version of a bug-fix can be matched to existing code in a repository and the after version is then recommended or automatically applied. Thus, the first criterion ensures that there is a before version of a code snippet such that it can potentially be compared to existing code. The second criterion focuses on the comment and ties to our motivation of explainable recommendation. Instead of just notifying a developer of a potential change to their code, it would be more useful to tell them why this change is needed. This means that the comment must be understandable on its own and is not too specific to the context of the original question in the thread. Again, the two authors independently labeled usefulness of the 1,482 confirmed pairs and discussed any disagreements.

Finally, to provide external validation for the pairs we mark as useful, we select around 3 useful comment-edit pairs from each tag for a total of 15 pairs and submit corresponding pull requests. Table 8 includes the descriptive statistics of the categories on these 15 comment-edit pairs per tag. We wrote a script that uses the GitHub search API to find repositories that match the following criteria:

1. The repository’s main programming language matches that of the tag
2. The repository was pushed to in the last 90 days
3. The repository has at least five stars
4. The repository has at least one closed pull request

These criteria help find active repositories with a higher likelihood of having our pull requests reviewed. After finding these potential repositories, the script then searches each file in these repositories to find exact code matches of the “before” version of the target comment-edit pair. We manually check any identified files to make sure that we can propose a change that is similar to the edit of the comment-edit pair. After finding a promising file, we make a pull request that performs a similar change to that in the edit with the description of the pull request being the exact comment, if possible, or a slightly
Table 8: Categories and tags of the 15 comment-edit pairs used to make pull requests

| Category   | Java | Javascript | Android | Python | Php | Total |
|------------|------|------------|---------|--------|-----|-------|
| Solution   | 2    | 1          | 0       | 0      | 1   | 4     |
| Question   | 0    | 1          | 0       | 0      | 0   | 1     |
| Extension  | 0    | 1          | 0       | 0      | 0   | 1     |
| Flaw       | 1    | 1          | 0       | 1      | 2   | 5     |
| Correction | 0    | 0          | 2       | 1      | 0   | 3     |
| Obsolete   | 0    | 0          | 0       | 1      | 0   | 1     |
| **Total**  | 3    | 4          | 2       | 3      | 3   | **15** |

paraphrased version in order to make it more grammatically correct or understandable in a pull request context. For example, on answer 52517618, we paraphrase this comment “On Java 7 you can also use new String(bytes, StandardCharsets.UTF_8); which avoids having to catch the UnsupportedEncodingException” to “Using new String(bytes, StandardCharsets.UTF_8) avoids the possibility of throwing an UnsupportedEncodingException.” Our artifact page 20 contains links to all our submitted pull requests.

Results. Table 5 shows the descriptive statistics of our useful labeling. Our Cohen’s kappa ranged from 0.62 - 0.81 across the tags, and was 0.74 across all pairs. Out of the 1,482 confirmed pairs, we found only 396 (27%) useful ones. We identify two main reasons for this low percentage. The first is that in many cases, the edit adds a new code snippet. For example, a comment points out an alternative way of accomplishing the task or an alternative API to use. Instead of updating the existing snippet, the edit adds an extra code snippet stating that this is another option to use. In this case, there is no “before” version of this code snippet and thus, it will not satisfy our first criterion. The second common reason was that the comment is too specific to the commenter’s context. For example, in post 4605982, this comment caused an edit: “layout_height="fill_parent" in combination with layout_below on ListView and layout_alignParentBottom on LinearLayout is correct and should work.” However, this comment is too specific to what the original poster is asking for. Not every developer will necessarily want to have that same layout. Thus, we marked that pair as not useful since it does not make sense outside of the question context.

To better understand the characteristics of the useful pairs, we look deeper into the category information in Table 7. The second column under every tag shows the number and percentage of the confirmed pairs in the corresponding category that were marked as useful. The results show that while pairs of type Error are the most frequent, only 27% of them are useful. This is mostly due
to the error being specific to the context of the post; for example, reporting that the desired behaviour/functionality is not working correctly.

On the other hand, the Correction category shows both a high frequency and a high percentage of usefulness (67%). While pairs of typeObsolete, Extension and Flaw were not frequent, their usefulness was particularly high at 59 - 67%. Not surprisingly, the usefulness of pairs of type Request, Disagree, and Question is quite low (1 - 11%). Given that the nature of these types of pairs is inherently specific to the post context, it is not surprising that they would not be useful in wider applications. These results suggest that to increase the potential usefulness of comment-edit pairs, we may need to devise additional techniques that can specifically identify comment-edit pairs in the promising categories. We discuss this further in Section 8.

Of the 15 pull requests made to unique open source repositories on GitHub, 9 requests have been accepted and merged into their respective repository, 4 requests are still awaiting responses, and 2 requests were rejected. Of the nine requests that were accepted, five of the comments taken from Stack Overflow needed to be paraphrased. The original Stack Overflow comment usually contained references specific to the context of the answer and would not make any sense on the pull request. For one of the two pull requests that were rejected, one of the developers replied that the repository is no longer maintained. The other rejected pull request was closed with no comment.

Finally, as a note in terms of tangledness of the identified 396 pairs, only 39 (10%) of these were tangled. This is aligned with the overall low tangledness of edits on Stack Overflow.

**RQ4:** Out of 1,482 confirmed comment-edit pairs across the five tags, 396 (27%) were potentially useful. The usefulness of comment-edit pairs varies by category and devising automated techniques to find pairs in promising categories may increase the chances of finding useful pairs. Additionally, to date, 9 out of the 15 pull requests we submitted to further demonstrate usefulness were accepted.

8 Discussion

In this paper, we built tooling to identify comment-edit pairs on Stack Overflow. Our goal was to investigate if these comment-edit pairs could potentially be used as an additional source of explainable bug-fix/code-improvement data. In this section, we discuss our findings and the opportunities and challenges for further extending this line of work.

8.1 Applications

*Software Engineering Applications.* Bug detection, bug localization, program repair, and additional (code) recommender tools provide important support
Can We Use Stack Overflow as a Source of Explainable Bug-fix Data?  

for software developers. Bug fixes or API usages mined from commit history are often used to build \[44\] or evaluate \[45\] these techniques. Comment-edit pairs extracted from Stack Overflow can help these systems in several ways. Our results show that the mined comment-edit pairs rarely have multiple unrelated changes (i.e., tangled changes). Thus, our work opens the door for more focused bug-fix data sets. Recent work \[30\] already leverages answer edits for creating data sets of code errors and corrections, but it focuses only on syntax errors that are found through compiling various versions of a snippet, and thus does not try to associate reasons for the changes. As our results in \[RQ3\] show, there are many categories of changes that occur in the comment-edit pairs we analyzed, ranging from bug fixes to code style and generalizability improvements in the flaw and extensibility categories.

Second, the fact that a Stack Overflow edit is accompanied by a corresponding comment means that an explanation can be provided to the developer about why a specific code snippet is problematic or why an alternative method of solving something might be simpler or more efficient. This is as opposed to commit messages that are either typically short, not always descriptive, and often link to a bug report or associated issue. For example, in answer \[26933338\] from Android, the initial provided answer includes a snippet of the manifest file that includes both WRITE_EXTERNAL_STORAGE and READ_EXTERNAL_STORAGE. The snippet is then edited to remove the latter permission. If such a removal is suggested to a developer, it will likely not make sense without a concrete reason. The mined comment that is associated with the edit to this answer is “If you have the WRITE_EXTERNAL_STORAGE permission you don’t need READ_EXTERNAL_STORAGE [...]”. When suggesting a fix to this piece of code, providing this comment can help the developer understand why the fix or suggestion is being made. We used this comment to make one of the accepted pull requests.

**Linked Stack Overflow Edit History** Recently, Stack Overflow introduced a new feature that shows a history symbol \[
\]
beside each question and answer. Clicking on this history symbol shows the activity history of the post. Relating the comments on the post to the edits in the history could be useful to help users understand why an edit was made. Thus, our matching algorithm can be also be applied in that context as future work.

### 8.2 Challenges and Opportunities

In the above, we discussed the potential applications of using the mined comment-edit pairs. However, these do not come without challenges since the nature of Stack Overflow data is different than what we traditionally see in version-control systems. In order to leverage this data source, the ultimate goal is to (automatically) differentiate useful and useless pairs. Such differentiation is difficult for multiple reasons. We discuss these reasons and potential solutions and/or future work opportunities we perceive.
Conversations. One challenge we came across during our manual validation is that there is often a conversation occurring in the comments section. Thus, while many of the comments we have analyzed are stand-alone (recall our second criterion for usefulness), many comments would be difficult to understand without the context of the rest of the conversation. Such comments would not be useful as explanations provided to users. The challenge here is to automatically differentiate these two types of comments while extracting comment-edit pairs. While this is a difficult problem, some ideas from the natural language processing (NLP) domain may be potentially useful. For example, some work looks at automatically inferring context in a sentence [46]. Such techniques can be used to check if the current comment refers to something from the previous comment. Another simpler technique is to not report comments that were posted within a specific time window (e.g., 30 seconds) from the previous comment. This is based on our observation that often, a user posts a big comment split across multiple consecutive ones due to space limitation.

Filler text. Another challenge related to the mined comments is that some comments are useful and provide a good explanation of the edit, but they contain “filler” text. This could be tagging another participant in the conversation (e.g., a comment from [53216022] “@Lothar For case-insensitive comparison, use comparing(Contact::getLastName, String.CASE_INSENSITIVE_ORDER). For language-sensitive comparison, use e.g. comparing(Contact::getLastName, Collator.getInstance(Locale.US))” or thanking someone for their help (e.g., a comment from Post [44470955] “@binariedM thank but i cant make it work. The console says: “Uncaught ReferenceError: Invalid left-hand side in assignment” in the line of “this = x.concat…””). While presenting such comments is still useful when accompanied with the edit, ideally, this filler text could be somehow automatically removed. There could be some NLP techniques to help with that and which can be investigated as future work.

Added code. Many of the comment-edit pairs we found have helpful suggestions and edits, but unfortunately, the edit is made as an added code snippet. This happens especially in the context of the Solution category where the answer poster typically adds the suggested alternative solution as another code snippet. These pairs are valuable but the main challenge is that there is no “before” version. Many of the answers contain multiple code snippets to, for example, break the steps to be taken or to separate the code that should go in multiple files or classes. Therefore, it is not clear which previous code snippet is the added code snippet an alternative for. However, there is typically descriptive text added on top of the new snippet and reasoning about such text may provide some opportunity to solve this issue. Obviously, an easier alternative that favors precision over recall would be to report only comment-edit pairs where the matched code element occurs in an existing snippet.

Incomplete code. Many code snippets on Stack Overflow do not include import statements that are necessary to make them compilable or to help in resolving
types. Resolving types is necessary for any recommender system to make use of the comment-edit pairs. This problem has been discussed before in other contexts and there is existing work that tries to infer types for Stack Overflow snippets (e.g., [47][48]).

**Pair categories.** We manually categorized our mined pairs. Our results show that some categories have more potential for usefulness than others. Thus, a future opportunity could be automatically categorizing pairs and only reporting pairs that fall in the promising categories. Since we share all our data, we foresee future research on designing machine learning classifiers that can automatically assign a category based on specific features of the comment and edit. While determining these features is not something we explicitly worked on in the context of this work, potential features we foresee from our observations include the size of the edit, the presence of certain keywords (e.g., does not work, error, exception etc), and how many regions/blocks (i.e., text vs. code) have been changed in the edit.

9 Threats to Validity

As expected with any empirical study, there are several limitations and threats to the validity of our results. We discuss them below.

**Construct Validity.** Since identifying comment-edit pairs relies on manual analysis, there is a risk that the comments and edits in the pairs we analyze are not actually related. We mitigate this by defining what a positive label means and by having two authors review the pairs and discuss disagreements. We also erred on the side of precision and confirmed matches only when we were sure. We share our exact labeling on our artifact page to facilitate replication and further analysis.

Whether something is useful or not is mostly subjective. In addition to defining an explicit coding guide and having the two authors independently decide on usefulness and discuss disagreements, we also use external validation of usefulness by submitting pull requests to open-source systems based on our data.

**Internal Validity** The regular expressions we used to identify code terms are taken from Treude et al. [40]. We modified this list to account for the other languages we analyze and based on experimenting with our ground truth. However, we cannot claim that the set of regex patterns are complete. While our precision was high, additional regular expressions may potentially catch more comment-edit pairs.
External Validity A potential threat to the generalizability of our results is that we analyze only 1,910 pairs. This decision was based solely on the amount of manual labor involved. Determining if a comment-edit pair is correct and gathering additional data about its usefulness, category, and tangled changes takes on average 1.5 min. Thus, the two authors spent close to 95 hours to manually analyze the 1,910 pairs. Additionally, we took an additional 8 hrs (approximately 1.5 hours per tag) to resolve conflicts since conflict resolution involved more discussion. Creating the separate ground truth set also took around 26 hrs, since both authors needed to analyze all comments and edits for each selected answer. Thus, the manual labor involved with our current data is already around 129 hrs, or the equivalent of 16 working days. That said, the sample of 1,910 is a statistically representative sample of all the detected pairs.

We also analyze only 5 Stack Overflow tags. While these are popular tags on Stack Overflow and span four different programming languages, our results may not necessarily generalize beyond that.

Another limitation relates to the pull requests made on open source GitHub repositories. We make a small number of pull requests (15) which do not establish comprehensive usability of these pairs. However, the goal of these pull requests was not to be comprehensive but to provide external validation and confidence in the usefulness of the pairs. Although these pull requests provide this confidence, there is inherent bias due to the methodology we use to select pairs and find the potential repositories. Since we used exact code matching in order to find potential repositories instead of a more thorough and precise code parsing approach, we were limited to searching for simple and easily fixable code patterns. Thus, we do not know how pull requests for more complicated changes might be received by developers.

10 Conclusion

In this paper, we study comment-edit pairs extracted from Stack Overflow answers. We implement a technique for identifying comments that resulted in edits to code blocks in the answers. We run this technique on five popular Stack Overflow tags and share 248,399 resulting comment-edit pairs on our artifact page [20]. We then manually validate a statistically representative sample of 1,910 randomly selected comment-edit pairs and confirm 1,482 of them. We then categorize these 1,482 pairs and also determine their usefulness and whether the edits are tangled.

We find that the edits are rarely tangled (only 11%) and that 27% of the confirmed pairs are useful. Our results show that categories such as Correction, Extension, and Flaw are particularly useful. Since we share our data set, future work may explore automatically classifying comment-edit pairs such that only those from promising categories are reported. We conclude that Stack Overflow may indeed be used as an additional source of information for mining bug-fix/code-improvement data sets that can be used in various types of code
Can We Use Stack Overflow as a Source of Explainable Bug-fix Data?

recommenders and software engineering applications. We already show that the type of comments and edits we find there have been useful for getting pull requests merged in open-source repositories. All our data and code are available online [20]. We hope that this data along with the discussion we provide about future extensions and opportunities encourages further research in this area.

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