Fault Localization Using Textual Similarities

Zachary P. Fry and Westley Weimer
\{zpf5a, weimer\}@cs.virginia.edu
University of Virginia

Abstract. Maintenance is a dominant component of software cost, and localizing reported defects is a significant component of maintenance. We propose a scalable approach that leverages the natural language present in both defect reports and source code to identify files that are potentially related to the defect in question. Our technique is language-independent and does not require test cases. The approach represents reports and code as separate structured documents and ranks source files based on a document similarity metric that leverages inter-document relationships.

We evaluate the fault-localization accuracy of our method against both lightweight baseline techniques and also reported results from state-of-the-art tools. In an empirical evaluation of 5345 historical defects from programs totaling 6.5 million lines of code, our approach reduced the number of files inspected per defect by over 91%. Additionally, we qualitatively and quantitatively examine the utility of the textual and surface features used by our approach.

1 Introduction

Maintenance tasks can account for up to 90% of the overall cost of software projects [9, 17]. A significant portion of that cost is incurred while dealing with software defects [35]. Large software projects typically use defect reporting systems that allow users to submit reports directly; this has been shown to improve overall software quality [2, 36]. User-submitted defect reports vary widely in utility [21]; reports go through triage to allow developers to focus on those reports that are most likely to lead to a resolution. We propose a system to make the maintenance process more efficient by reducing the cost of localizing faults by leveraging this user-provided information.

Fault localization is the process of mapping a fault (i.e., observed erroneous behavior) back to the code that may have caused it. Performing fault localization is relatively time consuming [41] and thus costly. For this reason, many existing techniques attempt to facilitate this process. In general, such techniques rely on test cases [1, 13, 23, 37, 42], model checking [6, 7], or remote monitoring [31, 32]. These approaches may not be directly applicable to user-submitted defect reports, since reports rarely provide a full test case or program trace [21].

In this paper, we address the cost of such localization for user-submitted defect reports. We present a lightweight approach that maps defect reports to source code locations. Our approach relies primarily on textual features of both
source code and defect report descriptions, although it takes advantage of certain additional information (e.g., stack traces, version control histories) when they are available. Notably, it does not require test cases, compilation, execution traces, or remote sampling, all of which can potentially limit the applicability of other fault localization strategies.¹

Our approach is based on several underlying assumptions about the textual features of both source code and defect reports. With respect to code, we assume that developers choose identifier names and comment text that are representative of observable program behavior. For defect reports, we assume that the reporters use a vocabulary based on their observations of program behavior — a vocabulary that will thus be in some ways similar to developers’, although reporters may not have access to the source. Finally, we hypothesize that a defect report and a code location are more likely to pertain to the same fault if they are similar in terms of word usage; we formalize this in a similarity metric.

The main contributions of this research project are thus:

– A lightweight, language-independent model that statically measures similarity between defect reports and source files for the purpose of locating faults. This comparison is based on a structured textual analysis of the natural language in both documents.

– A large empirical evaluation of our technique including 5345 real-world defects from three large programs totaling 6.5 million lines of code — over an order of magnitude larger than the evaluations in previous work [13, 23, 37]. Our approach reduces the number of files developers inspected per defect by 91.5%, outperforming baselines such as using user-reported stack traces (53.1%) and previously-published results.

– A quantitative and qualitative explanation of our technique’s success. Notably, we show that factors such as the reported priority or the number of duplicate reports present are not related to our model’s success. Instead, we find that human word choice determines the performance of our model, thus supporting our hypothesis that the vocabulary chosen by developers and reporters can be used to localize faults.

The structure of this document is as follows. In Section 2, we motivate our approach by presenting an example fault with its associated defect report and source code. Section 3 outlines our approach and formally defines how we measure the relative similarity between code and defect report text. Next, Section 4 presents a detailed empirical evaluation of our approach. Section 5 places our work in context. Finally, Section 6 concludes.

2 Motivating Example

In this section, we present an example defect report taken from the Eclipse project. This example illustrates the potential benefit of matching the natural

¹ Strictly speaking, this paper presents a defect localization approach, but fault localization is the term of art used for this line of research (e.g., [1, 23, 37, 42]).
language in a defect description with keywords from the source code for the purpose of identifying the defect’s location.

User-submitted defect reports typically consist of a free-form textual description of the fault. When presented with such a defect report, it is up to the developer to derive and locate the cause of the undesirable behavior. This requires thorough familiarity with the code base; for large projects, an important part of the triage process is finding which developer is most likely to be able to resolve a given defect report [3]. There are significant differences among developers in terms of how quickly they can locate a given fault [41]. Our goal is to narrow the source code search space that the developer needs to consider, thereby decreasing the software maintenance cost overall.

Consider the following defect report from the Eclipse project, defect #91543, entitled “Exception when placing a breakpoint (double click on ruler).” The description is as follows:

```
With M6 and also with build I20050414-1107
i get the stacktrace below now and then when
wanting the place a breakpoint when double
clicking in the editor bar. if i close the
editor and reopen it again it goes ok.

!MESSAGE Error within Debug UI:
!STACK 0
org.eclipse.jface.text.BadLocationException
   at
org.eclipse.jface.text.AbstractLineTracker.getLineInformation(AbstractLineTracker.java:251)
   ...
```

Initially, a developer might be inclined to inspect code implicated directly. In this case, one might check the `AbstractLineTracker` file and other files in the stack trace, or search the list of all files that reference a `BadLocationException`. Additionally, one might scan the files that were changed prior to either of the particular builds mentioned. Finally, based on basic searching (using a tool such as `grep`) one might uncover any of the following files: `Breakpoint.java`, `MethodBreakpointTypeChange.java`, `BreakpointsLocation.java`, and `TaskRulerAction.java`, among hundreds of others. This example illustrates that the search space is large, even when a programmer uses the defect report’s specific information.

In the actual patch for this defect, developers edited only two source files. `ToggleBreakpointAction.java` contained the majority of changes that addressed this defect report, with one minor change to a call-site in `RulerToggleBreakpointActionDelegate.java`. Some of the methods in those files include:

```
ToggleBreakpointAction(..., IVerticalRulerInfo rulerInfo)
ToggleBreakpointAction.reportException(Exception e)
RulerToggleBreakpointActionDelegate.createAction(
```
The identifier names associated with these two files show clear language overlap with the report above. For example, even when only the report title and the method names are considered, key words such as `breakpoint`, `exception` and `ruler` occur in both sets. When examining the overall word similarity, the two files that were changed for the fix are among those files most similar to the text in the defect report. Using textual similarity not only avoids unrelated methods considered by traditional search techniques [20], but further limits the fault localization search space by trimming files with coincidental or narrow language overlap. Aggregating overall word similarity ensures that only documents with considerable and meaningful similarity are favored.

The log messages associated with software repositories represent another possible source of human-chosen natural language information to leverage when localizing faults. The `ToggleBreakpointAction.java` file accumulated seventeen log messages over four years worth of changes. Examples of these log messages include:

- "Can't set a breakpoint on the first line of an editor"
- "Allow multiple debuggers to create breakpoints using the same editor."
- "NullPointerException when trying to set breakpoint (in ToggleBreakpointAction)"

Terms such as `breakpoint`, `editor` and `exception` occur in both the log messages and the defect report, suggesting that this file may be relevant. Repository log messages are typically written in plain natural language which can be extracted with minimal analysis effort, much like comments in source code. Furthermore, repository log messages are written to chronicle the changes made to a given source code file. In addition, as many of these changes attempt to address previous defects, it is reasonable to assume they might contain specific terms taken from previous defect reports themselves.

We hypothesize that prioritizing the search space by ranking files of interest in this manner can greatly facilitate fault localization — using only static, natural language information, such as the defect report, source code and log messages. In the next section, we present a model to take advantage of this intuition.

### 3 Methodology

Our goal is to reduce the cost of software maintenance, focusing on fault or defect localization. The available input includes a defect report describing a fault, as well as static textual software development artifacts, such as the project source code and revision history. The desired output is an ordered list of source files that are likely to contain the cause of that fault.
To fix the defect in question, such a list can be explored directly or further refined, depending on size of the system and resources available. While the resulting lists can still be quite large and must be processed manually, previous work has shown that such filtering localizations are helpful [6]. More specifically, over a similar set of defect reports accompanied by lists of methods (i.e., backtraces or counterexamples), humans were shown to take less time to address those defect reports in which an additional tool-generated annotation narrowed that information down to a smaller number of lines [43, Fig. 5]. Fault localization information might also be used as an attachment on the original defect report: in a study of over 27,000 historical defect reports, those including similar attachments and comments (e.g., backtraces or lists of methods) were more likely to be resolved rapidly [21, Fig. 7].

Since defect reports and development text have different formats, we propose to map both of them to structured document intermediate representations. These intermediate representations reflect, but simplify, the structure of the original documents. We then build a model based on pairwise relationships between subparts of each document, and rank each source file accordingly. In Section 3.1 we formalize a general document representation and then explain how we compare various sub-representations in Section 3.2. Finally, we formalize the overall technique in Section 3.3.

3.1 Structured Document Representation

Both defect reports and source files are represented as distinct structured documents. In this paper, we use structured document to denote a set of ⟨name, value⟩ pairs (called “features”), where values are well-typed and drawn from non-overlapping parts of the original artifact. The types considered include number, string, list of strings, and term frequency vector. A term frequency vector is a mapping from terms (i.e., words) to the frequencies with which they appear in a given text. Term frequency vectors are often used in natural language processing; we use them to represent unbounded freeform text such as defect report descriptions or source code comments.

We map defect reports to our intermediate form directly. Defect reports are structured natural language files containing multiple parts, such as title, description, optional stack trace, project versions affected, and operating systems affected [21]. We first focus on the natural language title and description. We break the text into a list of terms by splitting on whitespace and punctuation and converting each term to all lowercase characters; we then construct term frequency vectors from the resulting multiset of words. Additionally, we also parse and record categorical data, such as the operating system and software version, representing them as discrete values in the structured document (e.g., as strings and numbers). Finally, we parse any stack traces into ordered sequences of strings.

Source code, which is not expressly written in natural language, is handled similarly, but with a few extensions that have been shown to be effective in previous work involving textual analysis [39, 45]. We obtain an initial list of terms
by splitting on whitespace and punctuation. However, we obtain further refined terms by taking advantage of paradigms such as Hungarian notation, camel case capitalization, and the use of underscores to separate terms in a single string [39]. For example, given the string “nextAvailableToken” we increment frequencies for the following terms: “next”, “available”, “token”, and “nextAvailableToken”.

Source files are also structured and can also be decomposed into substructures. Substructures include method signatures, method bodies, comments, and string literals, among others. In addition to the overall term frequency vector for the entire file, each substructure is processed separately into its own term frequency vector. Thus our intermediate representation for a source file will include a term frequency vector for words in comments, one for words in method bodies, and so on.

Finally, many mature software projects also maintain revision information. We utilize two specific forms of version control information: human-written change log messages and frequency of revision (“code churn”). When a developer makes changes to one or more files, the common practice is to include an informative message when updating a central repository. These messages often explain both “what” the change does (e.g., “add bounds checks when receiving socket data”) and “why” it was made (e.g., “fix high-priority buffer overrun in networking code”) [11, 46]. These messages thus relate developer concepts and vocabulary to particular files, and can thus be used to aid fault localization.

The logs are parsed as basic natural language and included as a substructure of all relevant source files. Additionally, we record the dates at which a file is changed over the lifetime of the project as a source code feature to compare with the submission date of the defect report. This feature may be helpful in fault localization as previous work has shown that historical “code churn” is often a good predictor of which files will be changed in the future [34].

Once we have reduced the source code and the defect report to structured documents, we can compare their substructures pairwise to determine their similarity. Figure 1 shows an example of this overall approach, with only some of the pairwise comparisons highlighted. Next, Section 3.2 describes our approach to comparing term frequency vectors, and Section 3.3 shows our overall model for fault localization.

3.2 Textual Document Similarity

Intuitively, two documents are similar when their subparts have a large fraction of their terms in common. The more terms the two corresponding pieces of text share, we assume, the more related concepts they both describe.

In practice, some terms are more indicative of underlying similarity than others. For example, terms such as “int”, “class” or “the” may occur frequently in two unrelated documents. We wish to limit the impact of such terms on our similarity metric. However, since we desire a language-independent approach, rather than hand-crafting an a priori stop-list of common words to discount, we derive that information from the set of available defect reports and source code. Intuitively, two documents that share a rarer term, such as “VerticalRuler”,


Fig. 1. Architecture for fault localization via natural language. Defect reports and source code are mapped down to structured documents. The substructures can then be compared pairwise (not all shown) using separate metrics (e.g., the report title text might be compared to the source file method names using a term frequency vector comparison, while the report stack trace might be compared to the source file method names using a positional index). The overall similarity, and thus the fault localization rank of that source file, is the weighted sum of the substructure similarities.

should be measured more similar than two documents that share a common term such as “int”.

To formalize this intuition we use the term frequency — inverse document frequency (TF-IDF) measure [24], which is common in information retrieval tasks. We want to measure how strongly any given term describes a document with respect to a set of context documents. Given a document $d$ and a term $t$, the TF-IDF weighting is high if $t$ occurs rarely in other documents, but relatively frequently in $d$. Conversely, a low weight corresponds to a term that is frequent globally and/or relatively infrequent in $d$. The weight for a document $d$ and term $t$ is computed as follows:

$$
tf(t, d) = \frac{\text{# occurrences of } t \text{ in } d}{\text{size of } d}
$$

$$
idf(t) = \frac{\text{# of documents}}{\text{# of documents containing } t}
$$

Note that $idf$ is defined with respect to a corpus of available documents. In our experiments, when comparing against a given defect report, the corpus is taken to be all terms in all source files, log messages, and defect reports filed before that report in question. With the background formalisms thus described, we now explain how we combine them to aid fault localization.

In our approach, the overall similarity between a defect report and a source file is built up from the pairwise similarities between their substructures (e.g., term frequency vectors). We wish to empirically determine which pairwise comparisons are the most predictive of fault localization when the two structured documents in question are compared. For instance, previous work has shown
that defect report titles are highly significant when searching for duplicate reports [22]; we hypothesize that they may be similarly significant when attempting to locate defects. Section 3.3 describes such a weighting.

3.3 Our Technique

We build on a portion of the TF-IDF formalism to form our overall similarity metric:

$$\text{similarity}(v_1, v_2) = \sum_{t \in v_1 \cap v_2} v_1[t] \times v_2[t] \times \text{idf}(t)$$

For each term contained in both documents’ parts, we multiply the product of its frequencies in both documents subparts by that term’s idf weight. While we use idf in a standard way, we measure term frequency based only on the number of occurrences of a given term without normalizing based on document size. The aggregate sum over all words’ values then serves as the similarity measure for those two documents’ subparts.

A major distinction between this metric and standard approaches is that we do not normalize for the size of the documents. While normalization is natural in many information retrieval tasks, we claim that the special structure of source code and the fault localization task make it undesirable here. For example, consider a defect report that mentions the term “VerticalRuler” in a project where the only source code reference to that term occurs inside one very large source file. In such a case, we would like to report that single source file as very similar to the defect report. However, if the file’s size were normalized, it would appear to be less similar to the defect report than smaller files that share more common terms (e.g., “database”). Additionally, large projects often contain many code clones, and while not all cloning is harmful [25], much of it is inconsistent: for example, code clones are changed consistently a mere 45–55% of the time [28]. In standard information retrieval, near-duplicate text may be an uninteresting search result, but when looking for defects, near-duplicate code clones should all be considered. We want to account for the possibility of higher concentrations of code clones in larger files and not discount the associated natural language artifacts based on file size alone. In general, other works apply size-based normalization when large documents increase false positive rates or otherwise degrade the accuracy of a given method. We claim that the loss of precision associated with normalization outweighed the benefits it provided. This is in line with previous claims [39] that traditional information retrieval search techniques used for documents do not map perfectly to code-based textual analysis.

While the above technique is intended for use with two term frequency vectors, we require certain adaptations for other types of structured data. Categorical data, such as operating system flavors or program versions, are treated as a vector with a single term and the metric can be used in the standard fashion. Stack trace vectors — sequences of strings representing method names — are compared as word vectors by using the inverse positional index of a method in the call trace name as its frequency (thus weighting the first method the highest).
Finally, we incorporate the idea of code “churn” into the technique as it has shown to correlate with defect density and is readily measurable given a source repository [34]. Formally, we measure a source file’s degree of “churn” by counting the number of times the file was changed during a set window of time. In our experiments, we used the entire available source history as the time window, equating code churn with the number of changes that had been checked in against a file. Similar to categorical data, we treat “churn” as a vector with a single term.

Given a defect report $D$ and set of source files $f_1 \ldots f_n$, our goal is to produce a rank-ordered list of the files, weighted such that files likely to contain the defect are at the top. Human developers then inspect the files on the ranked list in order until the fault has been localized. The rank of a file $f_i$ is given as follows:

$$\text{rank}(D, f_i) = \sum_{v_j \in D} \sum_{v_k \in f_i} c_{jk} \text{similarity}(v_j, v_k)$$

where $v_j$ ranges over all of the term frequency vectors in the defect report’s intermediate representation, $v_k$ ranges over all of the term frequency vectors in the source file’s intermediate representation, and each $c_{jk}$ is a weighting constant for that particular vector pair. The $c_{jk}$ constants are the formal model: a high value indicates that similarity in the associated pair of sub-substructures (e.g., defect report title paired with source code comments) is relevant to fault localization.

One approach would be to use machine learning or regression to determine the values for the $c_{jk}$ weightings. The size of our dataset, which includes tens of millions of datapoints and all terms in over 48,000 files and 6.5 million lines of code, precludes such a direct approach, however. Attempts to apply linear regression to the dataset failed to terminate on a 36 GB, 64-bit eight-core 3.6 GHZ machine within four hours. For scalability, we instead use several common statistics as a starting point for a parameter space optimization to obtain a model (see Section 4.2).

4 Evaluation

We conducted two main experiments to evaluate our approach. The first directly compares the accuracy of our technique to other lightweight baselines at file-level localization and indirectly compares to state-of-the-art techniques. The second experiment quantitatively verifies our hypothesis that fault localization via textual analysis depends significantly on human word choice.

4.1 Subject applications and defects

The experiments used three large, mature open source programs and 5345 total defect reports, shown in Figure 3.

We chose these projects for several reasons. First, they are relatively indicative of substantial, long-term real-world development in terms of size (at least 6.5
### Table 1. Distribution of source files with defects

| Project (Date checked out)       | Source files with defects | Total source files | Percentage |
|----------------------------------|---------------------------|-------------------|------------|
| Eclipse (2009.09.08)             | 2660                      | 21303             | 12.49%     |
| Mozilla (2009.09.08)             | 1811                      | 6179              | 29.31%     |
| Openoffice (2009.09.22)          | 1463                      | 1507              | 97.08%     |
| **Total**                        | **5934**                  | **28989**         | **20.47%** |

**Fig. 2.** Distribution of files with defects throughout the subject applications. In this case, a file is said to contain a defect if it was changed in a repository revision that specifically mentioned fixing a certain defect, and addressing that defect involved only changes to source files.

million lines of code total) and maturity (each is 8 to 11 years old). Additionally, each project has both defect report and source code repositories.

For each program, we obtained the subset of the available defect reports for which we could establish a definitive link between the report and a corresponding set of changes to source files. We thus restricted attention to those defect reports that were mentioned by number in source control log messages. We additionally restricted attention to reports of actual faults, omitting feature requests and other invalid or duplicate reports filed using the defect report system. Also, we only considered defects for which all corresponding changes took place in source files (i.e., .java, .cpp, etc., but not .xml) in the main branch of each project (e.g., omitting changes to minor branches, testing branches, or data files). Accordingly, the numbers for “files used” and “code used” in Figure 3 correspond to source files in trunk of each project’s repository. Finally, we excluded files or reports that could not be processed (e.g., from CVS or parsing errors).

To avoid over-fitting the model to our chosen data set, we split the defects into separate training and testing subsets. To train the model, we selected 450 (8%) of the defects that occurred first chronologically across all three projects. The model was created and refined using only these preliminary defects and the remaining 4915 defects were held out to evaluate the model. This suggests that such an approach could be implemented by collecting a minimal number of initial defects while achieving high accuracy as reported in the following sections.

### 4.2 Parameter space optimization

Our first step is to build a model relating similarity comparisons between defect report and source code structures to fault localization. In the terminology of Section 3.3, this involves determining values for the 34 distinct $c_{jk}$ weights.

---

2 Eclipse’s /cvsroot/eclipse; Mozilla’s /cvsroot; OpenOffice’s / trunk.

3 We could have used cross-validation [27] instead to help detect bias from over-fitting, but prefer to use holdout validation because of the large number of available datapoints and the time-series nature of the data: defect reports often make reference to previous defect reports [21, 22]. It would not be valid to train a model on future defect reports and evaluate it on past ones.
| Program  | Total Defects Used | Files Used | Lines of Code Used | Language(s) | Avg. report length (lines) | Avg. report title (words) |
|----------|--------------------|------------|--------------------|-------------|---------------------------|--------------------------|
| Eclipse  | 1,272              | 23,601     | 3,476,794          | Java        | 172.535                   | 8.642                    |
| Mozilla  | 3,033              | 14,651     | 2,262,877          | Java, C++   | 316.811                   | 9.428                    |
| OpenOffice| 1,040              | 9,992      | 815,473            | Java, C++   | 60.547                    | 5.623                    |
| Total    | 5,365              | 48,244     | 6,555,144          | -           | -                         | -                        |

**Fig. 3.** Subject programs used in our evaluations. “Defects” counts reports that could be linked to a particular set of changes. “Files” counts retrieved source files in the project branch, including those not involved in defect reports. “Lines of Code” measures the size of those source files, while “Languages” lists their programming languages. The last two columns measure aspects of the defect reports used.

To build such a model we first performed a one-way analysis of variance (ANOVA) on a subset of the data to estimate the predictive power of each possible document comparison. For each defect report we consider all of the files that were eventually fixed by the developers and also 150 files, chosen at random, that were not. We pair each such file $f_i$ with the original defect report $D$ to produce one datapoint. Each datapoint has multiple associated features (i.e., the explanatory variables): there is one feature for each each of the 34 $\langle v_j, v_k \rangle$ vector pairs, with the measured similarity serving as the feature value. The response variable for a given datapoint is set to 1 if the file was modified by developers and 0 otherwise.

An ANOVA measures the ratio of the variance explained by each model feature (i.e., each $\langle v_j, v_k \rangle$ similarity) over the variance not explained. We use this ratio only as a starting point for $c_{jk}$; distant values will merely yield a longer training search time. These ANOVA values may not be optimal because our final model goal is to rank order the files for fault localization and not to minimize the error between a model and the artificial 0 and 1 response variables.

The second step was to perform a principle component analysis (PCA) to determine the number of components that were relevant to the task of detecting the location of a fault in source code. Given our 34 possible document substructure comparisons, this analysis showed that a combination of 15 accounted for more than 99% of the overall variance in the data. The final $c_{jk}$ values were obtained via a gradient ascent parameter space optimization. In each iteration, the best model available was compared to similar models, each constructed by increasing or decreasing the value of a single $c_{jk}$ by 10%. The comparison was conducted using the score metric detailed in Section 4.3. We terminated the process when the improvement between one iteration and the next was less than 0.01%; this took 5 iterations. We used the final $c_{jk}$ values as our formal model.

---

4 The inclusion of 150 files was chosen to be as large as possible while allowing the problem to be tractable on available hardware; see Section 3.3.
| Test Set          | # Defects | Our Approach | Stack Trace | Code Churn | Optimal Search |
|-------------------|-----------|--------------|-------------|------------|----------------|
| OpenOffice only   | 1018      | 82.728%      | 57.979%     | 72.755%    | 75.731%        |
| Eclipse only      | 1124      | 89.937%      | 56.295%     | 73.131%    | 91.155%        |
| Mozilla only      | 2773      | 95.359%      | 50.152%     | 93.860%    | 87.906%        |
| Stack traces only | 325       | 89.608%      | 65.060%     | 76.442%    | 90.683%        |
| Complete set      | 4915      | 91.502%      | 53.137%     | 84.820%    | 86.128%        |

Fig. 4. Score values for selected techniques. The “Test Set” column lists examined subsets of the 4915 defects from three programs; 450 separate defects were used as training in Section 4.2. “Our Approach” measures the score obtained by our technique. The “Stack trace” baseline favors files mentioned in user-provided stack traces, the “Code churn” baseline favors frequently-changed files, and the “Optimal search” baseline simulates an optimal code search based on defect report terms.

4.3 Experiment 1 — Ability to localize faults

Our first experiment measures the accuracy of our technique when localizing faults. We compare two versions of our technique against two baseline approaches directly. We also indirectly compare against the published results of three state-of-the-art tools using a common metric.

We adopt the score metric for measuring the accuracy of a fault localization technique. The score metric is commonly used in fault localization research [13, 23, 37]. As described in previous work, “the score defines the percentage of the program that need not be examined to find a faulty statement in the program.” [23, p. 6] For example, a ranking for an OpenOffice defect report that requires the user to inspect 2,000 of the 9992 files before finding the right file has a score of $(9992 - 2000)/9992 = 80\%$. Higher score values indicate better accuracy. We apply the score metric at the file level of granularity. We report the average score over all defects available.

Figure 4 shows the results. A lower baseline of 50\% represents inspecting files in random order. Our approach outperforms all baselines over the entire test set (highlighted in boldface in Figure 4) and is generally better than other approaches in most subsets. The “Stack traces only” subset includes all defect reports that featured stack traces. Note that of these 4915 defect reports used to evaluate our approach, only 325 (6.7\%) contained stack traces.

We compare against three baselines motivated in Section 2 by mimicking some steps developers might take when attempting to fix a defect. In each case we produce a ranked list and compute a score metric to admit a direct comparison with our technique. The code churn baseline ranks files in descending order of number of changes throughout the entire history of the system up to the date of the defect report in question. The stack trace baseline ranks files by their position in any stack trace provided as part of the defect report; all files not mentioned in the stack trace are equally likely to be chosen after all files mentioned in the trace. Finally, the optimal search baseline approximates a developer using a search tool with some degree of domain knowledge. Given a search term, such a tool can return a list of all source files mentioning that term, ignoring case, ranked by
number of occurrences. All files that do not contain the term are equally likely to
be chosen after any files that do contain the term. The optimal search baseline
considers every word in the defect report and uses the one that yields the best
score result (i.e., the search term that indicates all of the relevant files and as few
irrelevant files as possible). Note that the best search term cannot, in general, be
known a priori by an automated technique: using only the best term is meant to
represent human knowledge of the software system. While this baseline does not
perfectly model human code search, it approximates the process for the purposes
of comparison.

Over the entire test set, we outperform the stack trace, code churn and
optimal search baselines by 38%, 7%, and 5% respectively. While the perfor-
ance gain over a stack trace baseline is immediate, the lower performance gain
over code churn overall and over optimal search within the Eclipse and Mozilla
projects requires more of an explanation. Eclipse has the most source files out of
the three benchmarks. Additionally, as noted in Figure 2, the bugs are localized
to only 12.49% of the files. Both baselines thus have the potential to eliminate
much of the search space. However, the results for both baselines for OpenOffice
show that this is not the general case. In addition, since both external baselines
provide overall scores of over 84% and 86% respectively, only a 16-point and
14-point score increase is possible in either case. In that regard, our 7-point and
5-point increases constitute nearly 44% and 36% of the respective remaining
room for improvement. Finally, on large projects, even small gains are signifi-
cant: for example, the 7% score increase over the code churn baseline prevents
an aggregate of 4,501 source files (or 611,812 lines of code) from being considered
during the fault localization search over our entire test set.

Our technique performed most poorly on OpenOffice defects: if only Eclipse
and Mozilla are considered, our performance is almost 94%. This is explained by a
quirk of the OpenOffice project: their defect reports are about four times smaller
(see Figure 3), thus reducing one of the primary sources of textual similarity (see
Section 3.1).

The results presented in Figure 4 show that our tool outperforms lightweight
baselines. We also suggest that our technique may perform better than more
heavyweight techniques. Several state-of-the-art fault localization techniques re-
port accuracy values for their tools in terms of the distribution of subject faults
over the scale of possible score measures. For comparison purposes we use a
weighted average of each score interval to calculate an overall accuracy measure
for each approach. The tools of Jones et al. [23], Cleve et al. [13], and Renieris
et al. [37] achieved aggregate score measures of 77.797%, 63.415%, and 56%
respectively. The largest of these projects evaluated on 132 defects over seven
files containing at most 560 lines of code each. While these results are measured
on different test sets and are therefore not directly comparable, we note that
our technique obtains a score result 14 points higher than previous work and is
evaluated on an order-of-magnitude more defects and files.
| Document feature                              | Correlation with score |
|----------------------------------------------|------------------------|
| Average report length                        | 0.24                   |
| Maximum report length                        | 0.22                   |
| Defect lifespan                              | 0.20                   |
| Rate of commenting in edited source          | 0.18                   |
| Number of duplicate reports                  | 0.17                   |
| Report readability                           | 0.10                   |
| Number of edited source files                | 0.08                   |
| Reported priority                            | 0.07                   |

Fig. 5. Pearson correlation between surface features and our technique’s score.

Finally, our technique is lightweight in terms of execution time. Assuming code files are kept indexed as word vectors, our tool always runs in under 10 seconds per defect report and generally takes less than 1 second.

4.4 Experiment 2 — Human word choice

Our second experiment tests our hypothesis that our score accuracy is mainly due to correctly extracting and comparing the natural language chosen by humans in defect reports and source files. We first demonstrate that our technique’s accuracy is not dominated by other features, such as length, defect priority, or defect lifespan. Secondly, we alter the natural language of the subject reports systematically, showing that performance degrades in a proportional manner. Finally, we evaluate the relative predictive power of our model’s features.

We hypothesize that human-chosen natural language in defect reports and source code is a critical factor in our fault localization approach. We first discount several other potentially-prominent features in terms of predictive power with respect to the score accuracy of our technique. The features examined cover both defect reports and source code: the Flesch-Kincaid readability level of the report in question [18], the assigned defect priority, the number of total reports for a defect when considering all duplicates, the maximum report length for a defect, the average report length for a defect, the overall lifespan of the defect from reported defect to reported patch, the number of source files edited as part of the patch, and the rate of commenting in the edited source code.

We calculated the Pearson correlation of all 4915 total defects’ score measures with these features. The correlations can be found in Figure 5. It is generally accepted that correlations below 0.3 are not statistically significant [19]. All observed correlations fell well within these bounds and therefore we conclude that these features do not significantly affect our model. However, of all correlations, report length and rate of commenting had some of the highest relative values. This supports our claim that natural language is key to our technique’s success, since these features typically relate directly to the natural language present.

Next, we demonstrate that our model is greatly affected by the users’ choice of language in defect reports and the developers’ choice of language in source
code. To evaluate this, we measure our score accuracy as more and more human-chosen words are replaced by random words. We used three different random techniques to replace human-chosen words: replacing terms with words from the same general set (e.g., the set of all report description words), replacing terms with words from a different set (in this case, an English dictionary), and finally, replacing terms with strings of the same length made up of randomly selected characters (i.e., random noise). In each case, we altered the natural language in increments until the entire frequency vector had been changed, using the unaltered reports as a baseline. The results of this experiment can be found in Figure 6. Each datapoint represents the degradation in score of our algorithm running on the entire 4915-defect testing data subset with some fraction of each defect report’s text altered.

As the natural language in defect reports is changed, and thus the useful information in the report is reduced, the performance of our technique degrades. The reduction in score is not strictly proportional, as is expected from the presence of common words and our use of the idf weighting: retaining even a few words that account for some of the relevant document similarity in a given comparison degrades the performance of the tool only slightly. In addition, when replacing terms with words from a different corpus the performance initially increases very slightly and then decreases, following the other two replacement techniques. The sharp increase of degradation when all terms have been altered further reinforces the idea that our approach can perform accurately with even a small amount of natural language information and fails only when almost all information is changed. The general trend in Figure 6 is that performance of our approach degrades when natural language information is removed or altered. Thus, we posit that our approach is leveraging the human-chosen language and not additional features.

**Fig. 6.** The effect of replacing human-chosen words with various random words on our technique’s score over all 4915 defects in the test set.
Finally, having established that human word choice is critical, we evaluate which words and comparisons are the most important. Figure 7 shows the predictive power of the features in terms of a “leave-one-in” or “singleton” analysis.\footnote{The size of the dataset precludes a full ANOVA; see Section 3.3. In addition, heavy feature overlap precludes the use of a “leave-one-out” analysis; see PCA in Section 4.2.} To obtain these results we built many different versions of the model, each utilizing only one of the features. Thus, the score measure for each version suggests the relative utility of the given feature with respect to localizing faults.

The report title and body, as well as the method bodies and comments, are involved in many of the most useful relationships in our fault localization model. With respect to defect reports, the titles and bodies contain the majority of the natural language information chosen by the reporter and, as such, are more helpful than extraneous categorical data and stack traces. Comparatively, we believe that code revision log messages are helpful because they often address specific defects or defect reports and thus might use similar language. Code churn also proves to be predictive of defect location, supporting claims made in previous work [34]. Intuitively, code comments are effective when paired against terms from defect reports because they are both written explicitly in natural language and often encapsulate code specifications in a manner complementary to the language inherent in the code’s identifiers. Method bodies contain most of the text associated within code files and thus also serve as effective predictors. Finally, more obscure categorical information (e.g., processor architecture) and string literals found in code were less useful to the model.

\begin{table}[h]
\centering
\begin{tabular}{|l|l|l|}
\hline
Report Substructure & Code Substructure & Singleton score \\
\hline
Report body & Method bodies & 84.94 \\
Report date & Code churn & 84.82 \\
Report body & Log message & 84.51 \\
Report body & Comments & 83.60 \\
Component & Log message & 71.62 \\
Report title & Method bodies & 70.44 \\
Report body & Method signatures & 69.39 \\
Report title & Comments & 67.52 \\
Operating system & Comments & 67.31 \\
Component & Method bodies & 65.85 \\
Component & Comments & 64.76 \\
Report title & String literals & 60.69 \\
Report body & Class name & 57.10 \\
Stack trace & Class name & 53.14 \\
Report title & Method signatures & 52.59 \\
\hline
\end{tabular}
\caption{The score results from a “singleton” analysis in which we used only one feature and measured the score it achieves alone.}
\end{table}
4.5 Threats to validity

Although our experiments are designed to demonstrate that our technique performs well over a large number of defects and files, our results may not generalize to industrial practice. First, our benchmark programs may not be indicative. The programs we chose are all large, mature, open-source projects. While they span three individual domains, they may not generalize to all potential domains. Our results may not apply to younger, smaller projects, but we claim that fault localization becomes less interesting as the project shrinks (e.g., in the limit, fault localization is rarely a primary concern for a project with only a few small source files). In addition, all of our benchmarks involve GUI components, making them more likely to support our hypothesis that report-writers and developers will use similar textual terms. We view our evaluation on large datasets (e.g., ten times larger than previously-published evaluations [13, 23, 37]) as an advantage.

Bird et al. note that sampling defect reports for the purpose of experimentation may lead to biased results [5, 8]. As a result, our technique may only be good at localizing certain types of faults (i.e., those that open source developers deign to mention in version control logs). Lacking a project with a linked version control and defect repository, we cannot mitigate this threat beyond our claim that manual inspection of the reports found the faults to be a relatively even cross-section of each project’s repository over the history of that project (see Section 4.1).

Our code churn baseline may not be indicative because it relies on eight to ten years of version control information. For example, it may perform particularly well on the larger and older Mozilla project, correctly giving low rankings to the many files that have been stable for years. In practice, a development organization may not have such rich version history information, or such stable files may be manually excluded by developers.

Not all files in a project will be associated with fixed defects when using our selection methodology from Section 4.1. Previous researchers have noted that in practice, defects are not uniformly distributed [34]. If our model somehow learned the underlying defect distribution rather than using information from the defect reports, it would not generalize. We guard against this threat both by construction (i.e., our learned features are all coefficients for similarity metrics between defect report substructures and software development artifacts, and not development artifacts alone) and also by our use of holdout validation.

Finally, when comparing our results with those of established fault localization techniques using the score metric, we interpolated to convert previous distribution-style results to single score numbers and thus admit more illustrative comparisons. Previous publications have reported score value distributions over intervals from 0% to 100%. We estimated based on a weighted average of the medians of each interval. As a result, these indirect comparisons with previously-published results cannot used to draw firm conclusions and serve instead to provide descriptive context.
5 Related Work

Related research to our work falls into two main categories: prior work in fault localization, and prior work in reverse engineering.

5.1 Fault Localization

Ashok et al. propose a similar natural language search technique in which users can match an incoming report to previous reports, programmers and source code [4]. By comparison, our technique is more lightweight and focuses only on searching the code and the defect report.

Jones et al. developed Tarantula, a technique that performs fault localization based on the insight that statements executed often during failed test cases likely account for potential fault locations [23]. Similarly, Renieris and Rice use a “nearest neighbor” technique in their Whither tool to identify faults based on exposing differences in faulty and non-faulty runs that take very similar execution paths [37]. These approaches are quite effective when a rich, indicative test suite is available and can be run as part of the fault localization process. They thus require the fault-inducing input but not any natural language defect report. By contrast, our approach is lightweight, does not require an indicative test suite or fault-inducing input, but does require a natural language defect report. Both approaches will yield comparable performance, and could even be used in tandem.

Cleve and Zeller localize faults by finding differences between correct and failing program execution states, limiting the scope of their search to only variables and values of interest to the fault in question [13]. Notably, they focus on those variable and values that are relevant to the failure and to those program execution points where transitions occur and those variables become causes of failure. Their approach is in a strong sense finer-grained than ours: while nothing prevents our technique from being applied at the level of methods instead of files, their technique can give very precise information such as “the transition to failure happened when $x$ became 2.” Our approach is lighter-weight and does not require that the program be run, but it does require defect reports.

More recent work conducted by Wang et al. aims to refine the concept of fault localization based on test suite coverage metrics [42]. They closely examine contextual information to detect faults that are being executed but not identified.

Liblit et al. use Cooperative Bug Isolation, a statistical approach to isolate multiple defects within a program given a deployed user base. By analyzing large amounts of collected execution data from real users, they can successfully differentiate between different causes of faults in failing software [32]. Their technique produces a ranked list of very specific fault localizations (e.g., “the fault occurs when $i > arrayLen$ on line 57”). In general, their technique can produce more precise results than ours, but it requires a set of deployed users and works best on those defects experienced by many users. By contrast, we do not require that the program be runnable, much less deployed, and use only natural language defect report text.
Jalbert et al. [22] and Runeson et al. [38] have successfully detected duplicate defect reports by utilizing natural language processing techniques. We share with these techniques a common natural language architecture (e.g., frequency vectors, TF-IDF, etc.). We differ from these approaches by adapting the overall idea of document similarity to work across document formats (i.e., both structured defect reports and also program source code) and by tackling fault localization.

5.2 Reverse Engineering

Latent Semantic Indexing (LSI) is an information retrieval technique for measuring document similarity [14]. Similar to our technique, it uses word frequency vectors to measure co-occurrence of relevant terms in documents. Marcus and Maletic used LSI to expose document-to-source-code traceability [33]. While their work mainly focuses on matching documents from the initial phases of the development process, the work presented in this paper attempts to match specifically defect reports created by both users and developers throughout the maintenance process. Additionally, traditional LSI treats documents as a single, unified term frequency vector whereas our technique breaks documents down into substructures based on the hypothesis that certain language is more helpful for localizing defects.

Li et al. have examined the problem of extracting information from structured documents in addition to categorizing that information [30]. They focus on user queries in particular, which is similar to the defect reports we study in this work. They also note that tailoring analyses to specific corpora is particularly helpful, which we confirm with the use of inverse document frequency for weighting individual terms.

Devanbu et al. and Würsch et al. both developed software system search tools that leverage the natural language in both source code and related software artifacts [16, 44]. While our system has a similar back-end natural-language-based approach, our overall goal is automatic fault localization, not general code search or program comprehension.

Breu et al. studied the effect of user interaction throughout the defect fixing process [10]. Much like the work presented in this paper, they found that additional information and user clarification generally only serves to aid in fixing defects. While their focus is on the interaction between users and developers throughout the maintenance process, our work aims to measure the quality of information contained in different parts of documents associated with defect fixing.

Ko et al. have studied the overall process used by developers to find information and understand programs [26]. They employed a human study to gain insight into what kinds of information developers think is relevant to a given task and how they make decisions in this process. The goal of our research is complimentary to this work in that we are trying to automatically discern which information is related to specific defects and, in a broader sense, aid in the maintenance process on the whole.
Shepherd et al. focused on both proving that the natural language in source code is meaningful and also on attempting to extract those language artifacts in a meaningful and useful manner [39]. They studied natural language use in code for the purpose of developing a specialized code-search technique specifically focused on identifying distributed concepts throughout a system. Similarly, Lawrie et al. have examined the quality of source code identifiers in terms of code comprehension [29]. They show that insightful and carefully chosen natural language identifiers make for more understandable and maintainable code. We build upon such work by leveraging these facts in the domain of fault localization.

Much work has been done to measure the quality of natural language choices made by developers [12, 15, 29, 40]. Additionally, some of this work looks at restructuring or refactoring natural language artifacts in an attempt to reverse engineer the original developers’ intentions and aid program understanding. We claim that measuring the quality of natural language is orthogonal to the work we present in this paper. We are more concerned with the ability of the natural language in both defect reports and source code to localize faults, regardless of the language’s quality. While higher quality information may allow our tool to compare documents more accurately, our tool currently achieves very high accuracy without accounting for the quality of the underlying natural language.

6 Conclusion

We present a lightweight, scalable technique for localizing faults based on document similarities. We hypothesize that human-chosen natural language present in both defect reports and source code can be compared to identify potential fault locations based on natural-language descriptions. Our technique is entirely static and is language independent.

An empirical evaluation shows that our technique not only performs better than several baseline approaches, but is comparable to the state-of-the-art techniques without requiring significant overhead or a runnable program and a test suite. We also demonstrated that the word choice in natural language artifacts was truly the dominant factor in our approach.

A large empirical evaluation of our program on 5345 historical defects from three real-world programs totaling 6.5 million lines of code showed that we can reduce the search space for finding a fault by over 91% on average. We believe that this approach has the potential to significantly decrease the cost of fault localization, and thus software maintenance overall.

References

1. H. Agrawal, J. R. Horgan, S. London, and W. E. Wong. Fault localization using execution slices and dataflow tests. In Software Reliability Engineering, pages 143–151, 1995.
2. J. Anvik, L. Hiew, and G. C. Murphy. Coping with an open bug repository. In OOPSLA workshop on Eclipse technology eXchange, pages 35–39, 2005.
3. J. Anvik, L. Hiew, and G. C. Murphy. Who should fix this bug? In *International Conference on Software Engineering*, pages 361–370, 2006.
4. B. Ashok, J. Joy, H. Liang, S. K. Rajamani, G. Srinivasa, and V. Vangala. Debugadvisor: a recommender system for debugging. In *Foundations of software engineering*, pages 373–382, 2009.
5. A. Bachmann, C. Bird, F. Rahman, P. Devanbu, and A. Bernstein. The Missing Links: Bugs and Bug-fix Commits. In *Foundations of Software Engineering*. ACM, 2010.
6. T. Ball, M. Naik, and S. K. Rajamani. From symptom to cause: localizing errors in counterexample traces. *SIGPLAN Not.*, 38(1):97–105, 2003.
7. T. Ball and S. K. Rajamani. The slam project: debugging system software via static analysis. In *Principles of programming languages*, pages 1–3, 2002.
8. C. Bird, A. Bachmann, E. Aune, J. Duffy, A. Bernstein, V. Filkov, and P. T. Devanbu. Fair and balanced?: bias in bug-fix datasets. In *Foundations of Software Engineering*, pages 121–130, 2009.
9. B. Boehm and V. R. Basili. Software defect reduction top 10 list. *Computer*, 34(1):135–137, 2001.
10. S. Breu, R. Premraj, J. Sillito, and T. Zimmermann. Information needs in bug reports: improving cooperation between developers and users. In *Computer supported cooperative work*, pages 301–310, 2010.
11. R. P. Buse and W. Weimer. Automatically documenting program changes. In *Automated Software Engineering*, 2010.
12. B. Caprile and P. Tonella. Restructuring program identifier names. In *International Conference on Software Maintenance*, page 97, 2000.
13. H. Cleve and A. Zeller. Locating causes of program failures. In *International conference on Software engineering*, pages 342–351, 2005.
14. S. Deerwester, S. T. Dumais, G. W. Furnas, T. K. Landauer, and R. Harshman. Indexing by latent semantic analysis. *Journal of the American Society for Information Science*, 41:391–407, 1990.
15. F. Deissenboeck and M. Pizka. Concise and consistent naming. *Software Quality Control*, 14(3):261–282, 2006.
16. P. T. Devanbu, R. J. Brachman, P. G. Selfridge, and B. W. Ballard. Lassie—a knowledge-based software information system. In *International conference on Software engineering*, pages 249–261, 1990.
17. L. Erlikh. Leveraging legacy system dollars for e-business. *IT Professional*, 2(3):17–23, 2000.
18. R. F. Flesch. A new readability yardstick. *Journal of Applied Psychology*, 32:221–233, 1948.
19. L. L. Giventer. *Statistical Analysis in Public Administration*. Jones and Bartlett Publishers, 2007.
20. E. Hill, L. L. Pollock, and K. Vijay-Shanker. Automatically capturing source code context of nl-queries for software maintenance and reuse. In *International Conference on Software Engineering*, pages 232–242, 2009.
21. P. Hooimeijer and W. Weimer. Modeling bug report quality. In *Automated software engineering*, pages 34–43, 2007.
22. N. Jalbert and W. Weimer. Automated duplicate detection for bug tracking systems. In *Dependable Systems and Networks*, pages 52–61, 2008.
23. J. A. Jones and M. J. Harrold. Empirical evaluation of the Tarantula automatic fault-localization technique. In *Automated Software Engineering*, pages 273–282, 2005.
24. K. S. Jones. A statistical interpretation of term specificity and its application in retrieval. *Journal of Documentation*, 28:11–21, 1972.

25. C. Kapser and M. W. Godfrey. "Cloning Considered Harmful" considered harmful. In *WCRE*, pages 19–28, 2006.

26. A. J. Ko, B. A. Myers, M. J. Coblenz, and H. H. Aung. An exploratory study of how developers seek, relate, and collect relevant information during software maintenance tasks. *IEEE Transactions on Software Engineering*, 32:971–987, 2006.

27. R. Kohavi. A study of cross-validation and bootstrap for accuracy estimation and model selection. *International Joint Conference on Artificial Intelligence*, 14(2):1137–1145, 1995.

28. J. Krinke. A study of consistent and inconsistent changes to code clones. In *WCRE*, pages 170–178, IEEE Computer Society, 2007.

29. D. Lawrie, H. Feild, and D. Binkley. Quantifying identifier quality: an analysis of trends. *Empirical Softw. Engng.*, 12(4):359–388, 2007.

30. X. Li, Y.-Y. Wang, and A. Acero. Extracting structured information from user queries with semi-supervised conditional random fields. In *Research and development in information retrieval*, pages 572–579, 2009.

31. B. Liblit, A. Aiken, A. X. Zheng, and M. I. Jordan. Bug isolation via remote program sampling. In *Programming Language Design and Implementation*, June 9–11 2003.

32. B. Liblit, M. Naik, A. X. Zheng, A. Aiken, and M. I. Jordan. Scalable statistical bug isolation. In *Programming Language Design and Implementation*, pages 15–26, 2005.

33. A. Marcus and J. Maletic. Recovering documentation-to-source-code traceability links using latent semantic indexing. In *25th International Conference on Software Engineering*, pages 125–135, 2003.

34. N. Nagappan and T. Ball. Use of relative code churn measures to predict system defect density. In *International Conference on Software Engineering*, pages 284–292, 2005.

35. C. V. Ramamoorthy and W.-T. Tsai. Advances in software engineering. *IEEE Computer*, 29(10):47–58, 1996.

36. E. S. Raymond. The cathedral and the bazaar. In *Linux Kongress*, 1997.

37. M. Renieris and S. Reiss. Fault localization with nearest neighbor queries. In *Automated Software Engineering*, pages 30–39, 2003.

38. P. Runeson, M. Alexandersson, and O. Nyholm. Detection of duplicate defect reports using natural language processing. In *International Conference on Software Engineering*, pages 499–510, 2007.

39. D. Shepherd, Z. P. Fry, E. Hill, L. Pollock, and K. Vijay-Shanker. Using natural language program analysis to locate and understand action-oriented concerns. In *Aspect-oriented Software Development*, pages 212–224, 2007.

40. A. A. Takang, P. A. Grubb, and R. D. Macredie. The effects of comments and identifier names on program comprehensibility: an experimental investigation. *J. Prog. Lang.*, 4(3):143–167, 1996.

41. I. Vessey. Expertise in debugging computer programs. *International Journal of Man-Machine Studies: A process analysis*, 23:459–494, 1985.

42. X. Wang, S. C. Cheung, W. K. Chan, and Z. Zhang. Taming coincidental correctness: Coverage refinement with context patterns to improve fault localization. In *International Conference on Software Engineering*, pages 45–55, 2009.

43. W. Weimer. Patches as better bug reports. In *Generative Programming and Component Engineering*, pages 181–190, 2006.
44. M. Würsch, G. Ghezzi, G. Reif, and H. C. Gall. Supporting developers with natural language queries. In *International Conference on Software Engineering*, pages 165–174, 2010.

45. N. Yoshida, T. Hattori, and K. Inoue. Finding similar defects using synonymous identifier retrieval. In *International Workshop on Software Clones*, pages 49–56, 2010.

46. T. Zimmermann, N. Nagappan, and A. Zeller. *Predicting Bugs from History*, chapter Predicting Bugs from History, pages 69–88. Springer, February 2008.