Bug localization aims to reduce debugging time by recommending program elements that are relevant for a specific bug report. To date, researchers have primarily addressed this problem by applying different information retrieval techniques that leverage similarities between a given bug report and source code. However, with modern software development trending towards increased speed of software change and continuous delivery to the user, the current generation of bug localization techniques, which cannot quickly adapt to the latest version of the software, is becoming inadequate. In this paper, we propose a technique for online bug localization, which enables rapidly updatable bug localization models. More specifically, we propose a streaming bug localization technique, based on an ensemble of online topic models, that is able to adapt to both specific (with explicit code mentions) and more abstract bug reports. By using changesets (diffs) as the input instead of a snapshot of the source code, the model naturally integrates defect prediction and co-change information into its prediction. Initial results indicate that the proposed approach improves bug localization performance for 42 out of 56 evaluation projects, with an average MAP improvement of 5.9%.

Keywords changesets · bug localization · online topic modeling · software maintenance and evolution

1 Introduction

Locating and fixing software bugs has persisted as one of the most common and important tasks software developers face on a daily basis. In well organized software projects, all bug occurrences are reported and preserved in an issue tracker, while the resulting software modifications are stored in a version control system. To fix a bug, a developer first analyzes the bug report looking for hints about bug location and then explores the source code to identify a few potential bug-related locations for which undesired behavior is later confirmed through debugging. To aid the developer in this process, and reduce time consuming project browsing, researchers have proposed many approaches to link a bug report to a specific section of the project code using automated Information Retrieval (IR) techniques Kim et al. [2013a], Saha et al. [2013], Chaparro et al. [2017], Nguyen et al. [2011]. IR-based Bug Localization techniques create an index from the preprocessed source code files, and subsequently use the index to build an IR model representing the software. When a new bug report arrives it is preprocessed in the same manner as the source code files, and it serves as a query to the IR model, which retrieves the most relevant program elements.

With modern software trending towards continuous deployment and relying on dynamic repositories with extremely high code churn and number of contributing developers Potvin and Levenberg [2016], Bhagwan et al. [2018], Pradel et al. [2020], new challenges for IR-based Bug Localization come to the forefront. First, the vast majority of prior work on IR-based Bug Localization has relied on files or methods taken from a snapshot of the source code, typically the most recent release of the software. However, as the software changes and evolves rapidly, the index and the IR model built on the snapshot of the source code becomes quickly outdated which can lead to the loss of bug localization effectiveness. At the same time, re-creating the index and the model incurs significant cost even on the latest hardware Lee et al. [2018] and leads to increased latency when retrieving the results Rao et al. [2013]. To introduce the dynamics of software
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Researchers have recently investigated using changesets (or commits) as the main unit of data used to construct retrieval models [Wen et al., 2016; Corley et al., 2018; Lin et al., 2021; Rao et al., 2013]. The advantage of changeset-based techniques is that they allow for continuous updates to the bug localization model, such that the model is built incrementally (or online) as changesets arrive, and captures all information about the source code at any given point in time. Online Bug Localization is a new perspective on bug localization that uses changesets to avoid costly retraining as the software changes.

Secondly, given that the modern software is a result of efforts of multiple participants (e.g., developers, testers, end users) with varying level of knowledge and expertise, bug reports may include different types of information, which has been observed to have a strong influence on the performance of IR-based bug localization techniques [Wang et al., 2015; Rahman and Roy, 2018]. Bug reports differ based on how they describe the software failure, e.g., when bug reports are written by expert developers they tend to include detailed information about the source of the bug, such as stack traces or even direct references to relevant source code artifacts [Mills et al., 2020]. Bug localization for such bug reports is most effective when it relies on simple token matching between the bug report text and source code. Another subset of bug reports, likely created by end-users that are unfamiliar with the software design or source code, provide only high-level description of the observed faulty behavior [Hooimeijer and Weimer, 2007]. For this second category of bug reports more sophisticated bug localization techniques that, e.g., mine revision histories or build higher-level representations of the source code, are required. In this paper, we describe an adaptive approach that is able to adjust to the type of content present in the bug report of interest.

To perform bug localization for rapidly evolving software and in the presence of diverse bug reports, this paper proposes JINGO, a model for online bug localization based on a streaming variant of the Latent Dirichlet Allocation (LDA) topic modeling technique [Blei et al., 2003], which has been previously employed by Corely et al. [Corley et al., 2018] for the purpose of feature location. To capture the evolution of software artifacts and bug reports over time, we use two parallel Online LDA models, one that tracks changes in the source code repo and another that tracks bugs reported in the issue tracker. The models 1) naturally represent development activity, including frequently changed and co-changed program elements; 2) effectively handle streaming data, including the ability to deemphasize older information; and 3) raise the level of abstraction into topics, which provide a higher-level structure for detecting related artifacts. Translating between the probabilistic topic spaces maintained by the two models is performed using a translation matrix, primarily constructed from the history of fixed bug reports and their corresponding changesets. JINGO adapts its prediction to the content of a bug report by emphasizing one of the probabilistic topic spaces. More specifically, the more code-like tokens are present in the bug report, the more weight is given to the LDA tracking source code. Conversely, if the bug report consist primarily of natural language, JINGO relies more on the LDA tracking bug reports and translation matrix for the prediction.

The main contributions of this paper are:

- Online, up-to-date model for bug localization that integrates adaptability to different types of bug report content.
- Dataset of high code churn open-source Java repositories with mapping of bug reports to their fixing changesets.
- Evaluation results using our dataset and an established benchmark of software projects with various development history lengths. The model and our experiments are available for further research as part of our replication package.

JINGO is situated in the current state of the art in the following way. Wen et al.’s technique (Locus) was the first to build a bug localization model based on changesets, with considerable success [Wen et al., 2016], however, their model was not designed to be frequently updated. Corley et al. were the first to explore the concept of continually updated LDA model based on changesets [Corley et al., 2018]. Compared to Corley et al., we introduce an online bug localization technique that is adaptable to the diversity of bug reports observed in modern software repositories [Catolino et al., 2019; Zhang et al., 2018].

2 Background

The bug localization problem is often framed as an Information Retrieval (IR) problem: given a text of a bug report (i.e. query) find the most appropriate program elements (i.e. documents). Popular IR approaches like the vector space model, which model a document using the frequency of each term in the document (term frequency) and the corpus (document frequency), are often used due to their simplicity and effectiveness [Kim et al., 2013a; Mills et al., 2018; Wen et al., 2016]. The vector space model requires that the exact words that appear in the query (bug report) are matched.

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1 https://github.com/aciborowska/jingo
in the document (program element). On the other hand, other IR techniques, e.g., topic models or neural networks, build a higher-level representation of the corpus content and use it as a reference point for comparing individual documents [Nguyen et al., 2011; Wang et al., 2018; Huo and Li, 2017; Xiao et al., 2018]. One such technique is Latent Dirichlet Allocation (LDA), which models a set of documents probabilistically via a set of topics that appear in those documents [Lukins et al., 2010]. Using LDA, the similarity between the bug report and program element is computed after they are both projected into the topic space, i.e. a query and bug report match if they express a similar distribution of topics. Another popular group of techniques are based on neural networks, however, compared to LDA, these techniques are less interpretable and have higher training computational cost. Most IR techniques, including LDA, assume a static corpus of documents that does not change significantly over time. On the other hand, Online Bug Localization recognize the evolution of documents (i.e. source code) over time and uses online model which can be efficiently update with a stream of newly arriving data (i.e. changesets, which capture modifications to the source code).

Online LDA. Latent Dirichlet Allocation (LDA) is a Bayesian probabilistic model designed to discover latent topics in large document corpora [Blei et al., 2003]. Based on a collection of documents, LDA infers latent document-topic distribution and a corresponding topic-word (or topic-term) distribution, such that each document is represented as a mixture of topics, and each topic is described by a mixture of words (or terms). Inferring document-topic and topic-word distributions is equivalent to training LDA and produces an interpretable model that can be applied to previously unobserved documents to extract their lower-dimensional representation. LDA is configurable via two main hyperparameters, \( \alpha \) and \( \beta \), affecting the smoothness of document-topic and topic-word distributions. Hyperparameter \( \alpha \) influences the document-topic distribution, such that increasing the \( \alpha \) value causes a document to express more topics, whereas lowering \( \alpha \) makes a document to be represented by fewer topics. Conversely, hyperparameter \( \beta \) influences the topic-word distribution. Raising \( \beta \) causes words to relate to multiple topics, while lowering \( \beta \) produces more specific topics with words rarely repeating between topics.

Updating LDA with a new document requires retraining the entire model from the beginning. As this process introduces significant time delay and computational cost, ordinary LDA is inappropriate for use in streaming environments where new documents, such as bug reports or changesets, arrive continuously. Therefore, to model the dynamics of modern software development, we use a recently devised variant of LDA, Online LDA [Hoffman et al., 2010], which allows to incorporate new documents through a update procedure, without the need for complete model retraining. Online LDA introduces the hyperparameter \( \kappa \), which influences how quickly older information in the document stream is forgotten. Increasing \( \kappa \) causes the pace of forgetting to rise, thus older documents have smaller impact on the current topic distributions.

LDA on Changesets. IR models like LDA can be trained and applied on separate, but closely related datasets, which reflect a similar vocabulary of terms. In this study, we follow the methodology proposed by Corley et al. [Corley et al., 2018], that is to train an LDA model on changesets, and infer topic distributions of program elements (e.g., classes) from a snapshot of the same repository to compare them to the topic distributions of bug reports in order to perform bug localization. Such a model would retrieve program elements to the developer. Alternatively, the LDA model can both train on changesets and retrieve changesets to developers. Wen et al. argued that presenting the developer with a changeset may provide contextual clues that are not available when retrieving program elements, however, most bug localization techniques focus on retrieving program elements [Wen et al., 2016]. The model requires no change to alternate between these two configurations, as these operations are performed on the already trained LDA model.

3 Motivation

In this section, we aim to motivate the need for the two key characteristics of our bug localization technique, 1) online bug localization that tracks rapidly-changing modern software, and 2) adaptability to the differences in bug reports observed in software repositories.

3.1 Online Bug Localization

As software changes are committed into a repository, the version control system computes changesets (or diffs) between the original and changed software files. Each changeset includes the content of lines that were added, removed or modified across all of the project’s files, and a commit message that provides a summary of the change in natural language. Commonly, changesets also include lines of context before and after each change. The set of changesets for a particular project contains a superset of the information contained in any one snapshot of the source code repository. In other words, all information available in a snapshot of the software can be reconstructed from the change history [Alali et al., 2008].

In this paper, we use output of the `git diff` command with default settings, which uses the default (i.e. Myers) diff algorithm.
Table 1: How the co-change relationship between classes is reflected in a LDA model built from changesets. The figure reports the average cosine similarity of different categories of co-changed classes, where the similarity is computed using the inferred LDA distribution of the text of each class.

| Average cosine similarity of classes | co-changed >= 20% of time | co-changed < 20% and >= 5% of time | co-changed < 5% of time |
|-------------------------------------|---------------------------|------------------------------------|------------------------|
| BookKeeper                          | 0.571                     | 0.172                              | 0.056                  |
| OpenJPA                             | 0.418                     | 0.152                              | 0.059                  |
| Pig                                 | 0.591                     | 0.198                              | 0.062                  |
| ZooKeeper                           | 0.251                     | 0.132                              | 0.107                  |

In simple terms, Online Bug Localization allows for building an up-to-date model for retrieving program elements based on the most current version of the source code, i.e., HEAD in each developer’s local copy of the software repo, rather than on prior versions. We deem that most of the time, the current version represents the source code that the developer cares about, rather than past snapshots reflecting a recent release of the software. To confirm the previous statement, we conducted a small survey on Reddit, asking the question “When working on finding the location of a user-reported bug, what version of the software do you use most of the time?”. The question was posted in the r/AskProgrammers, r/SoftwareEngineering and r/AskProgramming subreddits. More than two thirds of the respondents, 21/31, indicated that they use “The most recent version of the software from version control”, while 10/31 indicated they use “The version of the software in use by the reporting user”. One of the respondents further stated that “I start with trying to reproduce the bug with the most recent version. If I can’t, then I rollback to the version it was reported on to try to recreate it. I do quick and dirty until quick and dirty doesn’t cut it.” Another one noted that “I work with desktop applications, which are obfuscated and optimized, so debugging the released version can be difficult and time consuming”. Yet another respondent indicated a continuous deployment style of software engineering, i.e., “I do web projects so I use the version in the repo, in my node_modules folder. It doesn’t matter what’s latest, because my app is using the version is was compiled with.”. Overall, we note that developers prefer to start bug localization process by using the current version of the source code.

3.2 Advantages of Changesets

A key design choice in IR-based techniques that are applied to source code is what constitutes a document: classes, methods, files, or changesets. The document choice has a strong influence on, e.g., how topics in LDA model are formed, therefore utilizing changesets as documents brings several advantages inherent to this data type.

Co-changed code. Changesets have the benefit of capturing co-change code, which is known to be an important predictor of software maintenance activity [Hassan and Holt, 2004]. When leveraging changesets as a primary document dimension, co-changed code entities will often appear within the same document boundary. In the result, techniques utilizing co-occurring terms, like LDA, can recognize code entities that are often modified together leading to better IR performance. To understand the relationship between co-changed program elements, we empirically examine whether frequently co-changed classes are likely to be expressed by similar distributions of topics in a LDA model. For this purpose, we divide the co-changed classes in 4 different popular software projects (BookKeeper, OpenJPA, Pig and ZooKeeper) into three categories: 1) class pairs that are co-changed more than or equal to 20% of the time; 2) class pairs that are co-changed less than 20% of the time but more than or equal to 5% of the time; and 3) class pairs that are co-changed less than 5%. For instance, a class pair is considered co-changed more than or equal to 20% of the time, when the classes share at least 20% of commits in their respective modification histories. For each of these three categories of class pairs, we compute the cosine similarity of the topic distribution vectors of the class pairs using LDA model built from all of the changesets in each project. To limit the computational time and avoid corner cases, we only consider the 100 most changed classes for each project. Higher cosine similarity among frequently co-changed classes indicates that the co-change relationship is also reflected by the LDA model trained on changesets. The results, shown in Table I, demonstrate that the more often classes are co-changed, the more similar are their topic distributions, which indicates that the LDA model is able to inherently reflects the co-change relationship.

Frequently changed code. Another similar advantage is in frequently changed code, which is likely to appear in many documents. Researchers and practitioners have observed that, over time, bug disproportionally appear in code that has been recently and frequently changed [Memon et al., 2017; Graves et al., 2000]. Therefore, observing recent code changes, rather than only considering static source code snapshots, can have significant value to bug localization techniques.
3.3 Heterogeneity in Bug Reports

The content of bug reports can vary as some reports provide explicit localization hints through stack traces or code element names, while others contain only high-level textual description [Rahman and Roy, 2018]. To illustrate the different types of bug reports and their properties, in Figure 1 we show three exemplary bug reports we encountered when examining reports from the BookKeeper project. Each example contains a summary and description of the bug report and a list of fixed classes, sorted by the number of changed lines.

**Summary:** GarbageCollectorThread exiting with ArrayIndexOutOfBoundsException.

**Description:** After completing compaction, GarbageCollectorThread will do flush any outstanding offsets. When there is no offset present, its throwing following exception and exiting.

```java
[stack trace]
at org.apache.bookkeeper.bookie.GarbageCollectorThread
$CompactionScannerFactory.flush
(GarbageCollectorThread.java:175)
```

**Fixed:** GarbageCollectorThread

(a) BookKeeper-700; code references (CR) bug report.

**Summary:** AutoRecovery should consider read only bookies.

**Description:** AutoRecovery Auditor should consider the readonly bookies as available bookies while publishing the under-replicated ledgers. Also AutoRecoveryDaemon should shutdown if the local bookie is readonly.

**Fixed:** Auditor, BookKeeperAdmin, BookieWatcher, BookiesListener, AuditorRecoveryMain, ReplicationWorker

(b) BookKeeper-632; shared terms (ST) bug report.

**Summary:** Fix for empty ledgers losing quorum.

**Description:** If a ledger is open and empty, when a bookie in the ensemble crashes, no recovery will take place (because there's nothing to recover). This open, empty, unrepaired ledger can persist for a long time. If it loses another bookie, it can lose quorum. At this point it's impossible for the bookie to know that its an empty ledger, and the admin gets notified of missing data.

**Fixed:** Auditor, ReplicationWorker, AutoRecoveryMain, BookKeeperAdmin, AuditorElector

(c) BookKeeper-742; natural language (NL) bug report.

Figure 1: Three bug reports with different characteristics.

Figure 1a displays bug report #600, which describes a situation causing the GarbageCollectorThread to throw an exception and provides the resulting stack trace. To fix this bug, a developer modified waitEntrylogFlushed() method in the GarbageCollectorThread by adding a check for the offset size. This bug report provides a comprehensive source of information for the developer as it directly points to the class to be fixed, with additional information on finding the method to fix available in the stack trace. We refer to this type of bug reports as code references (CR) bug reports.

Bug report #632, shown in Figure 1b, refers to the correct way of handling "readonly bookies when publishing ledgers". To fix the bug, the developer modified multiple classes, some of which were already mentioned in the report’s text. We observed numerous common tokens shared between the bug report and modified classes: readonly, available, bookie, publish. Bug report #632 highlights that bug reports, even if not providing explicit localization hints, still often contain common tokens that, when grouped into topics, reflect higher-level similarity between concepts presented in the bug report and in the source code, thus we refer to this type of bug reports as shared terms (ST) bug reports.

Figure 1c shows bug report #742, describing a chain of faulty behaviors starting when "recovery is not performed for an open and empty ledger after bookie crashes". When fixing the bug, the developer modified multiple classes, none of which is mentioned in the report. This bug report poses the most challenging task for automated bug localization based on IR, since it provides only textual description with no code references and no unique terms that clearly map to source code locations. However, we observe that the set of modified classes for bug #632 and #742 is similar, indicating that there exists an upper layer abstraction that correlates the set of fixed classes to bug #742. In fact, after further examination of the bug fixing history, we noticed that this set of classes was frequently modified together in bug reports that were addressing similar topics. As these bug reports do not provide any code references and are expressed in natural language, we refer to them as natural language (NL) bug reports.
Analyzing the examples of different types of bug reports presented above led us to the following two observations. Firstly, bug reports display different levels of details, requiring adopting different strategies to maximize performance of automated bug localization [Rahman and Roy, 2018]. For instance, in the case of CR bug reports, it is sufficient to rely on matching code terms from a bug report to code tokens in a source code base. Conversely, ST bug reports can leverage topic similarity. However, neither of these approaches is able to address NL bug reports. This leads to our second observation, namely that even when common tokens or topics are not present, correlated high-level concepts are still expressed by the bug report and source code [Hooimeijer and Weimer, 2007] and can be identified by mining bug fixing history. In a results, a bug report can be matched to the most relevant code entities by examining bug fixing history to identify similar bug reports and their related code entities.

4 JINGO Model

Performing online bug localization requires the ability to operate in an environment where incoming changes are immediately integrated into a model, which is able to detect both simple (i.e., near exact terms) and high-level similarities between the code and bug reports. In this paper we introduce JINGO, a novel adaptable bug localization technique based on changesets. JINGO separately models the streams of bug reports and changesets with individual Online LDA models [Hoffman et al., 2010], obtaining two independent topic spaces, one for bug reports and one for changesets. To translate between the two topic spaces, JINGO constructs a translation matrix based on the history of previously fixed bug reports, which captures a mapping between high-level concepts expressed in bug reports and their corresponding fixed program elements.

The architecture of JINGO, depicted in Figure 2, allows for dynamically adapting to the three different types of bug reports described in Section 3. To this end, for a newly arriving bug report, JINGO uses its changesets model and bug reports model to infer two topic distributions respectively. The first distribution is directed towards CR and ST bug reports that share code references or common concepts with the code base. The second distribution targets NL bug reports through the multiplication via the translation matrix. The key idea behind the translation matrix is to utilize the bug fixing history in the project to capture the correlation between topics occurring in bug reports and in their relevant code entities. In other words, multiplying topic distribution of a bug report by the translation matrix results in a topic distribution of relevant code entities in the changeset topic space. Given that a bug report often include varying content, and hence, it is unlikely to be of only one type, we use a soft mechanism, based on the ratio of code tokens to all tokens in a bug report, to combine the two distributions. Finally, this combined distribution reflects the topics in the relevant code entities, and is used to select those elements in the code base.
4.1 Structure of the JINGO Model

JINGO is characterized by two parallel Online LDA topic models, one for changesets and the other for bug reports, and a matrix that translates from the bug reports to the changesets topic space, as shown in Figure 2.

**Changeset Model.** To build the changeset topic model, we use all changesets as they are committed into the source code repository. For every changeset, we use the output of `git diff` command, which includes basic changeset information (e.g. commit SHA, author, date) and a list of changed code hunks, across all of the project’s source code files, represented through added, modified or removed lines, each accompanied by 3 lines of context. We filter out the metadata and `git diff` boilerplate formatting, such as `+++`, `---` obtaining a set of file names and code modifications for each changeset [Amasaki et al., 2020]. Following a recommendation of Eddy et al. [Eddy et al., 2017], we decided to give more weight to file names by repeating them 10 times to emphasize their importance to the Online LDA. Finally, we follow the standard procedure to prepare source code for an IR model, including steps such as tokenization (using camel case and underscore), stemming using a Porter stemmer, and removal of standard programming language keywords, (e.g. if, for). In addition, we preserve the unsplit tokens into the corpus.

**Bug Report Model.** We train the bug reports topic model with new bugs as they are reported in an issue tracking system, e.g., JIRA. For each report, we first retrieve its summary and description. The summary is commonly a single sentence, while the description provides more details about the bug. Finally, before updating the model, for each bug report we perform a preprocessing procedure common for natural language text, including tokenization, stemming and English stop word removal. Similarly as when building changeset corpora, we also preserve unsplit camel case tokens to ease locating relevant files when explicit code references are included in the bug report.

**Translation Matrix.** A translation matrix - **T** - allows us to map from the bug report space to the changeset space, by simply multiplying a topic distribution inferred with the bug report model by the translation matrix, resulting in a projection into the changeset model’s space of topics. The use of a translation matrix was inspired by TM-LDA, a model based on LDA that intends to predict the expected future topics for a stream of documents [Wang et al., 2012].

To create the **T** matrix we leverage previously fixed bug reports and their corresponding changesets. The corpus of previously fixed bug reports provides an additional source of information that is leveraged by many approaches to bug localization, e.g. [Kim et al., 2013a, Rahman and Roy, 2018, Ye et al., 2014, Wang et al., 2020, Alkhazi et al., 2020]. However, the number of fixed bug reports depends on the size of the project and it is often very limited, thus using solely bug fixing history may not provide enough data to train the **T** matrix. To solve this cold-start problem, when building the **T** matrix we also include pairs of commit logs and changesets, since commit logs have been observed to contain substantial level of information describing in natural language the purpose or the functionality of the modified code [Wen et al., 2016].

We train the translation matrix using the following set of steps. First, for a set of fixed bug report - changeset pairs, and if necessary, commit log - changesets pairs, we infer a topic distribution for each fixed bug report using the bug report model and store it in matrix **B**, where the rows of the matrix correspond to the distribution inferred for each of the fixed bug reports and the number of columns in **B** corresponds to the number of topics in the bug report LDA model. Second, an analogous procedure is performed for the matching changesets. For these, the topic distribution is inferred by the changeset model and added to another matrix - **A**, with rows containing topic distribution of changesets and column corresponding to the number of topic in the changeset model. In this way, each fixed bug report - changeset pair creates one corresponding row in matrices **B** and **A** respectively. Finally, training the translation matrix **T** reduces to solving the following equation.

\[
T = \arg \min_T \|BT - A\|^2
\]

To solve the equation for the unknown **T** we perform least square minimization. Note that **T** is of size, number of topics in bug report model by number of topics in changeset model. Therefore, it requires at least as many rows in **A** and **B**, i.e., fixed bug reports, to compute. On the other hand, providing more than the required minimum amount of data to train the **T** matrix is desirable, as it is likely to increase the quality of mapping between topic spaces. We introduce a parameter specifying the minimum amount of data required to train the **T** matrix, \(\omega\), expressed as a multiplying factor of the (maximum) number of topics required in the topic models. For instance, \(\omega = 1.5\) and 50 LDA topics, would indicate that 75 fixed bug reports (or commit logs) are required to build the **T** matrix.

Once we determine the translation matrix, mapping between the bug reports to the changeset topic space is simple: we multiply the bug-related topic distribution for a new bug report by **T** matrix to get the equivalent distribution in changeset space. The computational cost of updating **T** over time is not large, and it is proportional to the number of fixed bug reports used. The cost can also be controlled by using a window based approach.
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4.2 Using JINGO for Prediction

Using a trained JINGO model, we follow the workflow in Figure 3 to perform bug localization for a newly arriving bug report. To start, we preprocess the new bug report to construct a query, using the same procedure as when building the bug reports corpus. We use the query to infer two topic distributions, one using the changeset model – changeset-related topic distribution, and another using the bug report model – bug-related topic distribution. To map the bug-related topic distribution from the bug report model to the changeset model, we multiply it by the $T$ matrix, obtaining a co-occurrence topic distribution. Note that, if the $T$ matrix is not trained due to lack of data, this step can be skipped and the final prediction is then based solely on the changeset-related topic distribution.

Bug reports typically include various content and are likely to be related to the code base in more than one way via, e.g., code element names, shared tokens or bug fixing history. Hence, we decide to combine the changeset-related topic distribution and the co-occurrence topic distribution to better reflect bug report’s characteristic. To this end, we adopt a weighting strategy based on the number of code tokens that appear in the bug report. A token is considered to be a code token if it is in a camel case format or it corresponds to one of class names in the source code base. We prioritize the importance of either of the distributions based on the intuition that the more code tokens are present in the bug report, the stronger is the similarity between the bug report and the source code base. If this is the case, we weigh the changeset-related topic distribution more strongly. On the other hand, if code tokens are rare and the bug report predominantly consists of natural language text, then the co-occurrence topic distribution becomes more significant, as it leverages topics co-occurrences patterns that are not directly connected to bug’s textual content. We use $\lambda$ to refer to the ratio of code tokens to the total number of tokens in a bug report. To account for the fact that natural language is more verbose in general and therefore the typical number of code tokens is much lower than the number of natural language tokens, we introduce an amplifying factor $\gamma$, which increases the importance of program element terms. We compute the combined topic distribution using the following equation:

$$dist_{combined} = norm(dist_{changesets} \ast \lambda \ast \gamma + dist_{co-occurrence} \ast (1 - \lambda))$$

Next, we use the changeset model to infer topic distributions for all documents in the most recent snapshot of the source code. As noted by researchers, bugs often pertain to small part of the code [Ye et al., 2014; Wong et al., 2014], thus inferring at the granularity of large source code files, e.g., classes, may negatively impact the performance of IR-based techniques. To solve this issue, we infer topic distributions of methods for each class and make a pairwise comparison against the combined topic distribution ($dist_{combined}$) of the query. Finally, each class is represented by a method that minimizes the cosine distance to the query and the classes are ranked according to increasing cosine distance to create a recommendation list.

5 Evaluation setup

5.1 Datasets: High Code Churn Dataset & Bench4BL

One of the key advantages of JINGO is the ability to perform quick model updates as the new data arrives, making it suitable for repositories exhibiting high code churn. To gauge JINGO performance for such projects, we curate a
High Code Churn Repositories (HCC-Repo) dataset by selecting open-source projects hosted on GitHub. To locate repositories of interest on GitHub, we perform a repository search query for all active Java repositories with at least one commit in 2019, and size of at least 10MB. Next, we sort the repositories in descending order by their code churn, calculated as the average number of commits per day, and select the top 10 repositories that use an explicit label to mark a reported issue as a bug (e.g., `bug, kind:bug`). To build a goldset that connects a bug report to its fixing changesets and to retrieve a list of modified files, for each project we manually investigate 20 randomly selected bug reports to identify the project’s convention for linking an issue to a changeset. In general, we note that developers tend to use keywords, such as “fixes”, “closes” or “resolves”, or a project name followed by an issue number. Hence, to link a bug report to its fixing commit, we test commit messages and pull requests against two types of regex, `keyword_#XXX` and `project_name-#XXX`, where XXX denotes an issue number. In the case of identifying multiple changesets for a bug report, we follow Bench4BL’s approach. Our final dataset of high code churn repositories, HCC-Repo, contains 10 projects and the total of 874 bug reports.

To observe how JINGO performs for repositories with more constrained commit traffic, we also use Bench4BL dataset [Lee et al., 2018], a collection of bug reports and corresponding lists of fixed source code files extracted from 51 open-source projects. The structure of the Bench4BL dataset allows for immediate use for evaluating release-based bug localization techniques, however it is not immediately suitable for an online approach. The key missing component in the dataset are the explicit connections between bugs and fixing changesets, which are necessary to perform evaluation in the online setting (i.e. timestamp-based). To this end, we adapted Bench4BL’s code to retrieve the required data in a way that maintains complete consistency with the original dataset. More specifically, following Bench4BL’s prior approach, to link a bug to a changeset we searched for an explicit mention of the bug identifier in the commit message. If more than one changeset was related to a bug, we selected the latest changeset, which is Bench4BL’s existing assumption. Due to difficulties when finding clearly discernible links between bugs and changesets, we excluded 5 projects from Bench4BL dataset: JBMeta, ENTESB, ZXing, WLFY and SOCIALI. Our final evaluation Bench4BL dataset is shown in Table 2 and consists of 46 projects and 2,125 bug reports.

| Group | Project | Commits | Evaluated version | Previously fixed bug | Fixed bugs in version |
|-------|---------|---------|------------------|---------------------|----------------------|
| Hyperparameter tuning projects | Corley | BookKeeper | 574 | 4.3.0 | 223 | 102 |
| | | OpenJPA | 4.616 | 2.3.0 | 1039 | 100 |
| | | Pig | 2.584 | 0.14.0 | 1063 | 155 |
| | | ZooKeeper | 1.245 | 3.5.0 | 368 | 235 |
| Total | | | 9.019 | — | 2,693 | 592 |
| Evaluation projects - HCC-Repo | DataHelix | 6.153 | — | 107 | 54 |
| | eXist | 18.612 | — | 286 | 86 |
| | Flank | 8.579 | — | 424 | 100 |
| | Hazelcast | 8.728 | — | 425 | 100 |
| | Magamela | 24.883 | — | 203 | 72 |
| | MegaMek | 18.899 | — | 163 | 100 |
| | Micronaut | 9.469 | — | 302 | 100 |
| | OpenJDK | 7.868 | — | 358 | 100 |
| | ShardinSphere | 27.014 | — | 383 | 100 |
| | WooCommerce4A | 10.658 | — | 102 | 62 |
| Evaluation projects - BENCH4BL | Codec | 1.387 | 1.5 | 13 | 11 |
| | Collections | 2.837 | 4.0 | 4 | 49 |
| | Compress | 1.033 | 1.4 | 41 | 12 |
| | Configuration | 2.743 | 1.7 | 66 | 31 |
| | Crypto | 548 | 1.0.0 | 1 | 8 |
| | CSV | 1.085 | 1.3 | 10 | 5 |
| | IO | 1.850 | 2.0 | 23 | 25 |
| | Lang | 5.231 | 3.5 | 217 | 40 |
| | Math | 5.795 | 3.0 | 74 | 39 |
| | Weaver | 429 | 1.3 | 0 | 2 |
| APACHE | Camel | 3.7986 | 2.15.0 | 1,298 | 147 |
| | Hbase | 16.015 | 2.0.0 | 446 | 418 |
| | Hive | 10.096 | 2.1.0 | 547 | 221 |
5.2 Metrics

To measure the effectiveness of our bug localization approach, we use three metrics commonly used in previous bug localization studies [Lee et al., 2018, Corley et al., 2018, Wen et al., 2016, Nguyen et al., 2011]:

- **Mean Reciprocal Rank (MRR)** reports on the average reciprocal rank for the set of bug reports. Given a bug report and a ranking of code elements, the reciprocal rank is computed as the multiplicative inverse of the first rank among the fixed classes. Intuitively, MRR quantifies techniques performance when locating the first relevant code element.

- **Mean Average Precision (MAP)** considers ranks assigned to all relevant code elements for a bug report. This metric captures techniques abilities to recommend all code entities that are related to a bug.

- **Top@k** metric expresses the accuracy of bug localization technique, when considering the top k positions in the ranking of code elements potentially linked to the bug report. The value of Top@k metric is calculated as the percentage of bugs for which corresponding relevant buggy code entities are located in the top k elements of the ranking.

5.3 Hyperparameter Optimization

Several researchers have highlighted the importance of hyperparameter tuning of topic models for software engineering applications [Agrawal et al., 2018, Treude and Wagner, 2019], therefore prior to the evaluation, we optimize hyperparameters using a separate dataset released as part of Corley et al.’s study [Corley et al., 2018]. The key parameters to optimize are shown in Table 3 and include the Online LDA priors for the two streaming topic models, and the set of parameters introduced by JINGO. First, we optimized the two Online LDA models independently using two metrics, perplexity and coherence [Binkley et al., 2014, Koltcov et al., 2014], and, second, we optimized the bug localization parameters based on the MRR metric. To decide on parameters values to investigate for the changeset model, we followed results reported in previous research [Corley et al., 2018]. In the case of the bug report model we used characteristics of the bug reports corpora, such as e.g., the number of documents and unique words, in relation to similar changeset corpora. For the decay factor we used three values that correspond to the minimum, mean and maximum possible value for that parameter. Note that, we did not optimize priors $\alpha$ and $\beta$ explicitly, relying instead on the automated estimation approach implemented in the gensim topic modeling library. We computed coherence and perplexity after training each topic model with 25%, 50% and 75% of the respective corpus stream, in order to avoid...
bias towards longer streams (or larger corpora), averaging the values of the metrics to assess the model’s performance. Finally, we selected the top parameters for both topic models.

Next, we searched over the parameters related to JINGO, namely \( \lambda \) and \( \omega \). The first parameter is a multiplying factor of the minimum number of fixed bug reports the model needs to observe before building the translation matrix. In the case of \( \lambda \), we selected a set of values based on similar experiments conducted by Wen et al. \cite{Wen2016}. Values marked with bold in Table 3 represent the set of final optimal values for all the parameters that we used during evaluation.

Table 3: Hyperparameters and their corresponding values used during grid search; selected, optimal values are in bold.

| Component          | Parameter                        | Value                   |
|--------------------|----------------------------------|-------------------------|
| Changeset model    | # topics - \( k \)              | \{75, 100, 150, 200\}  |
|                    | decay factor - \( \kappa \)     | \{0.5, 0.75, 1.0\}      |
| Bug report model   | # topics - \( k \)              | \{10, 25, 50, 100\}     |
|                    | decay factor - \( \kappa \)     | \{0.5, 0.75, 1.0\}      |
| Bug localization   | fixed bug reports factor - \( \omega \) | \{1, 1.5, 2.0\}         |
|                    | model combining factor - \( \gamma \) | \{1, 3, 5, 7\}         |

### 5.4 Experimental Procedure

To evaluate the performance of JINGO we simulate the development history of a specific software project, continuously updating the model with bug reports and changesets as they arrive. More specifically, the bug report model is updated every time a new bug is reported, while the changeset model is updated when a new changeset is committed into the repository. Additionally, when a bug fixing changeset is observed, we also update the translation matrix with the fixed bug report and the fixing changeset. Therefore, when evaluating for a specific newly arriving bug report, the changeset model contains all changesets that occurred before the time of the bug fixing commit, while the bug report model includes all bug reports reported before the commit timestamp.

To evaluate the statistical significance of the difference in performance between JINGO and the baseline, we compute the Wilcoxon signed-rank test with Holm correction and effect size using the Cliff’s delta \( \delta \). The values of \( \delta \) ranges from -1 to 1, where -1 implies that all values in the first group are larger than values in the second group, and +1 represents the opposite situation. The effect size was interpreted using the following criteria: (1) small effect = \( |\delta| > 0.147 \); (2) medium effect = \( |\delta| > 0.33 \); and (3) large effect = \( |\delta| > 0.474 \) \cite{Romano2006}. Note that in the case of small projects with number of bug reports equal or less than 10, we report the evaluation metric but did not conduct statistical testing.

### 5.5 Research Questions

**RQ1:** How accurate is JINGO in locating source code files relevant to a bug report? To answer RQ1, we use the proposed approach to identify buggy files in Bench4BL and high code churn datasets, and measure the effectiveness of JINGO with respect to the previously defined metrics. We compare the performance of JINGO against the online technique proposed by Corley et al. \cite{Corley2018}. Corley et al.’s technique has several similarities to JINGO, as it uses a single Online LDA model trained on changesets to locate program elements relevant to a given bug report. The main difference is in that JINGO models bug reports via a separate topic model and, through the usage translation matrix, incorporates information about previously fixed bug reports. Since Corley’s approach is based solely on Online LDA trained with changesets, we set its hyperparameters to values identified to perform best for the changeset Online LDA part of our model (as described in Section 5.2).

**RQ2:** What is JINGO’s time overhead required to update the model? The key advantage of using an online model is the ability to update the model with new data once it arrives. However, a key question remains: how rapid is an update procedure when compared to a full model rebuild? To answer this question, we collect the execution logs for all studied projects and, based on the recorded timestamps, we compute the time required to build and to update the model. Specifically, build time is the time required to build the model from scratch to the target version of the project we run the evaluation on, and update time reflects the time needed to update the model with one changeset (i.e., a single commit).

**RQ3:** How does JINGO compare to static (i.e., non online) bug localization techniques in terms of time overhead and accuracy? Most bug localization approaches proposed thus far use a static, snapshot-based model of the software. Although online models in general, and JINGO in particular, focus on updating a model as the software changes, we still need to contrast its bug localization accuracy to state of the art static models. In this research question, we compare
the accuracy of JINGO in retrieving relevant results to state of the art static approaches based on the Vector Space Model (VSM). We also quantify the time overhead to rebuild the model for such techniques and contrast it to JINGO.

**RQ4: Can JINGO adapt to different types of content in bug reports?** Bug reports have diverse characteristics and can embody different level of details, that, when leveraged, can increase the effectiveness of a bug localization technique. The aim of RQ4 is to investigate how well the proposed model captures different types of bug reports. To this end, we randomly sampled a set of 322 bug reports from our corpus (95% confidence level with a 5% margin error to the target bug report population). The sample spanned 40 different projects. Subsequently, one of the authors manually categorized each of the bug reports into one of the three groups (i.e., CR, ST, and NL). We report MAP and MRR scores contrasted to Corley’s et al.’s approach.
### 6 Results

Table 4: Evaluation results for JINGO compared to Corley et al. [Corley et al., 2018], denoted as Cor. The per-project higher value of a metric is highlighted by light gray background (n.nnn), Per-group of projects we used dark gray background (n.nnn) to highlight the higher value. Statistically significant increase in MRR and MAP values (p-value < 0.05) is marked with bold type with a superscript indicating the effect size: s – small, m – medium, l – large. Projects marked with † had less than 10 bug reports, thus statistical testing was not conducted.

| Project         | MRR Corley | MAP Corley | Top@1 Corley | Top@3 Corley | Top@5 Corley |
|-----------------|------------|------------|--------------|--------------|--------------|
| DataHelix       | 0.150      | 0.196      | 0.109        | 0.121        | 0.094        |
| eXist           | **0.123†** | 0.100      | **0.057†**   | 0.250        | 0.250        |
| Flink           | 0.269      | 0.308      | 0.178        | 0.195        | 0.172        |
| Hazelcast       | 0.386      | 0.324      | 0.235        | 0.219        | 0.280        |
| Magarena        | 0.111      | 0.104      | 0.085        | 0.073        | 0.026        |
| MegaMek         | **0.236†** | 0.106      | **0.152†**   | 0.076        | 0.182        |
| Micronaut       | **0.208†** | 0.158      | **0.148†**   | 0.120        | 0.131        |
| OpenDJ SDK      | 0.525      | 0.200      | 0.152        | 0.133        | 0.155        |
| ShardingSphere  | **0.172†** | 0.131      | **0.128†**   | 0.101        | 0.234        |
| WoolComm-4A     | **0.375†** | 0.140      | **0.194†**   | 0.093        | 0.295        |

Group average       | **0.225†** | 0.177      | **0.143†**   | 0.119        | 0.182        | 0.147        | 0.286        | 0.240        | **0.358†**  | **0.289†**

**CODERS**

| Project         | MRR Corley | MAP Corley | Top@1 Corley | Top@3 Corley | Top@5 Corley |
|-----------------|------------|------------|--------------|--------------|--------------|
| Codec           | 0.572      | 0.679      | 0.536        | 0.621        | 0.364        |
| Collections     | 0.299      | 0.519      | 0.490        | 0.548        | 0.490        |
| Compress        | 0.418      | 0.214      | 0.255        | 0.133        | 0.250        |
| Configuration   | **0.685†** | 0.512      | **0.482†**   | 0.379        | 0.548        |
| Crypto†         | 0.654      | 0.453      | 0.514        | 0.406        | 0.571        |
| CSV†            | 0.647      | 0.717      | 0.638        | 0.598        | 0.600        |
| IQ              | 0.694      | 0.627      | 0.674        | 0.565        | 0.560        |
| Lang            | **0.798†** | 0.449      | 0.719†       | 0.372        | 0.700        |
| Math†           | 0.584      | 0.613      | 0.474        | 0.453        | 0.462        |
| Weaver†         | 0.563      | 0.536      | 0.549        | 0.490        | 0.500        |

Group avg.       | **0.624†** | 0.539      | **0.533†**   | 0.449        | 0.504        | 0.414        | 0.692        | 0.577        | **0.742†**  | **0.679†**

**APACHE**

| Project         | MRR Corley | MAP Corley | Top@1 Corley | Top@3 Corley | Top@5 Corley |
|-----------------|------------|------------|--------------|--------------|--------------|
| Camel           | 0.258      | 0.272      | 0.181        | 0.192        | 0.163        |
| HBase           | 0.393      | 0.355      | 0.275        | 0.244        | 0.278        |
| Hive            | **0.248†** | 0.208      | **0.176†**   | 0.128        | 0.137        |

Group average       | **0.299**  | 0.278      | **0.211†**   | 0.188        | 0.193        | 0.183        | **0.329**  | 0.303      | **0.421†**  | **0.380†**

**SPRING**

| Project         | MRR Corley | MAP Corley | Top@1 Corley | Top@3 Corley | Top@5 Corley |
|-----------------|------------|------------|--------------|--------------|--------------|
| AMQP†           | **0.561†** | 0.221      | **0.381†**   | 0.172        | 0.417        |
| Android†        | 0.239      | 0.379      | 0.243        | 0.195        | 0.167        |
| Batch           | 0.463      | 0.621      | 0.288        | 0.377        | 0.320        |
| Batch Admin†    | 0.729      | 0.126      | 0.542        | 0.118        | 0.600        |
| Data Commons    | **0.569†** | 0.343      | **0.485†**   | 0.285        | 0.400        |
| Data GnomFire   | 0.645      | 0.532      | 0.357        | 0.315        | 0.520        |
| Data JPA        | 0.403      | 0.410      | 0.312        | 0.328        | 0.278        |
| Data MongoDB    | 0.531      | 0.418      | 0.367        | 0.303        | 0.357        |
| Data Neo4j      | 0.242      | 0.262      | 0.179        | 0.148        | 0.056        |
| Data Redis      | 0.586      | 0.505      | 0.393        | 0.271        | 0.500        |
| Data REST       | 0.449      | 0.504      | 0.362        | 0.314        | 0.273        |
| Framework       | 0.080      | 0.048      | 0.060        | 0.038        | 0.000        |
| Hadoop          | 0.394      | 0.434      | 0.300        | 0.308        | 0.222        |
| LDAP            | 0.427      | 0.258      | 0.351        | 0.163        | 0.250        |
| Mobile          | 0.668      | 0.543      | 0.634        | 0.510        | 0.500        |
| Roo             | **0.221†** | 0.184      | **0.191†**   | 0.141        | 0.119        |
| Security        | 0.469      | 0.410      | **0.356†**   | 0.311        | 0.328        |
| Sec. OAuth†     | 0.353      | 0.261      | 0.291        | 0.256        | 0.222        |
| Shell†          | 0.556      | 0.667      | 0.436        | 0.440        | 0.500        |
| Social†         | 0.554      | 0.571      | 0.483        | 0.474        | 0.500        |
| Social FB†      | 0.545      | 0.694      | 0.467        | 0.592        | 0.429        |
| Social Twitter† | 0.204      | 0.773      | 0.235        | 0.511        | 0.000        |
| Webflow         | 0.282      | 0.453      | 0.185        | **0.338†**   | 0.125        |
| Web Service     | 0.515      | 0.330      | 0.379        | 0.237        | 0.348        |

Group average       | **0.445†** | 0.414      | **0.345†**   | 0.298        | 0.310        | 0.294        | **0.501**  | 0.474      | **0.586**  | **0.550**
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6.1 RQ1: How accurate is JINGO in locating source code files relevant to a bug report?

Table 4 shows the performance of JINGO alongside Corley et al. [Corley et al., 2018] baseline with respect to 5 metrics: MRR, MAP, Top@1, Top@3, and Top@5. Statistically significant improvements in JINGO are marked with bold type with effect size (small, medium, large) noted in the superscript. Overall, JINGO demonstrates higher performance in locating buggy files across all of the above metrics with statistically significant increase of 6.3% and 5.9% for MRR and MAP respectively (p-value < 0.05). At a finer scale, we observe an improvement in the average results across all groups of software projects, with statistically significant difference in MRR and MAP values for the COMMONS, SPRING, ECLIPSE and HCC-Repo groups and MAP value for the APACHE group.

Specifically, JINGO achieves better performance in terms of MRR values for 37 out of 56 projects with a statistically significant improvement in 14 out of 43 projects that has more than 10 bug reports. In the ECLIPSE group, MRR results for all but one project were improved with statistical significance, increasing MRR score obtained by the baseline by 19.2%, 4.3% and 16.4% for jdt.core, pde.ui and platform.swt. In the case of org.aspectj, the baseline outperformed JINGO by 7.2%. We note the highest variance of increase and decrease of MRR values for the SPRING group, with JINGO outperforming the baseline in 13 out of 24 projects. Finally, in the HCC-Repo group, JINGO improved MRR scores for 8 out of 10 projects, including a statistically significant improvement observed for 5 projects.

Improvement in MAP values is achieved by JINGO for 42 out of 56 projects with statistically significant difference noted for 14 projects. Similarly as for the MRR metric, the highest MAP increase of 8.4% is observed for the COMMONS group with JINGO outperforming the baseline for all but one project. We also observe the ECLIPSE projects achieved significantly higher results when using JINGO with a small effect size. For the SPRING group, the proposed approach improves MAP results in 17 out of 24 projects. The improvement is statistically significant for 2 projects with medium (AMQP, Data Commons) and 2 with small (Roo, Security) effect sizes. In the HCC-Repo group, we note that JINGO outperforms baseline for 7 out of 10 projects with a significant improvement in 4 projects.

On average, JINGO outperforms the baseline for Top@1, Top@3 and Top@5 recommendation by 5.7%, 7.4% and 5.7% respectively. For 4 project groups, APACHE, SPRING, ECLIPSE and HCC-Repo, we observe that as we consider longer recommendation list the difference between the techniques is growing. However, for the COMMONS and WILDFLY groups, the difference between JINGO and Corley et al.’s approach reduces at Top@5 and Top@3 respectively.

6.2 RQ2: What is JINGO’s time overhead required to update the model?

Given the fact that JINGO is an online model, it is updated with each newly arriving data instance, keeping the model up-to-date with minimal time overhead. To investigate the performance benefit of using an online model over a model that requires re-building, in Figure 4 we show the time required to build and to update the model, averaged per each group of projects. Across all groups, we observe that the update time is significantly lower than build time, with the average speedup of 100 for the groups with smaller projects (SPRING and COMMONS), and up to about 1000 in the case of large projects (APACHE, ECLIPSE and HCC-Repo). This indicates that with the growing size of a repository, the cost of re-training the model becomes even more prohibitive. As an example, consider the results obtained for APACHE projects, with the average build time close to 20,000s = 5.5h and update time of about 22.5s. With new changesets being committed to a repository multiple times during a day, a model that relies only on re-building is outdated every couple of hours and consumes computational resources for a significant amount of time. On the other
Figure 4: Average time in seconds required to build and to update JINGO. Note that build and update time are illustrated with two independent y axes.

Table 5: Comparison between JINGO and two VSM techniques based on average (per bug report) accuracy and time overhead measures.

| Technique    | MRR  | MAP  | Build Time [s] | Update Time [s] |
|--------------|------|------|----------------|-----------------|
| JINGO        | 0.323| 0.241| 2964.955       | 4.786           |
| BLiA         | 0.371| 0.314| 101.315        | 101.315*        |
| BRTracer     | 0.471| 0.367| 91.245         | 91.245*         |

On the other hand, utilizing an online model with an update procedure significantly reduces the time overhead, hence allowing to incorporate new information as it arrives.

6.3 RQ3: How does JINGO compare (in terms of time overhead and accuracy) to static (i.e., non online) bug localization?

In order to compare JINGO’s bug localization accuracy to that of the state of the art static models, we select two recent techniques based on the Vector Space Model (VSM), BLiA [Youm et al., 2015] and BRTracer [Wong et al., 2014]. We used source code for both of these techniques that was shared as part of Bench4BL [Lee et al., 2018]. When considering all types of bug reports, simpler models like VSM have been reported to outperform LDA on bug localization [Rao and Kak, 2011]. Table 5 shows the average MAP and MRR for JINGO, BLiA and BRTracer on the Bench4BL set of repositories; we compute the average per bug report in order to account for some projects having more instances than others. Alongside the accuracy measures, Table 5 shows the average time overhead to construct the model and to update it with a single changeset, also averaged across all the projects in our dataset. BLiA and BRTracer do not have an update mechanism so the update time can be assumed to be equivalent to (re-)building the model.

BLiA and BRTracer outperforms JINGO in retrieval accuracy with the improvement in MRR of 4.8% and 14.8% respectively. On the other hand, JINGO offers significantly more time-efficient update procedure that is about 20 times faster than performing a full model rebuild for the VSM-based baselines. Although JINGO needs more time to initially construct the model when compared to BLiA and BRTracer, note that the build time depends on the number of documents. While BLiA and BRTracer use source code files (e.g., java class files), JINGO leverages changesets which are significantly more numerous compared to the number of classes, hence it is expected that JINGO requires more time to complete the initial build.
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Table 6: Performance on different bug report types from a manually annotated set ($N = 322$).

| Bug Report Type                  | Num. | JINGO MRR | Corley MRR | JINGO MAP | Corley MAP | diff  |
|----------------------------------|------|-----------|------------|-----------|------------|-------|
| Code References (CR)             | 165  | 0.455     | 0.365      | 0.090     | 0.376      | 0.266 |
| Shared Terms (ST)                | 100  | 0.257     | 0.272      | 0.015     | 0.180      | 0.177 |
| Natural Language (NL)            | 57   | 0.226     | 0.178      | 0.048     | 0.143      | 0.091 |

6.4 RQ4: Can JINGO adapt to different types of content in bug reports?

One of the key goals of JINGO is to adapt to different types of bug reports, namely Code References (CR), Shared Terms (ST) and Natural Language (NL) bug reports. Table 6 contrasts the accuracy of JINGO and Corley’s et al.’s approach for the manually annotated set of bug reports. In the case of CR bug reports, JINGO improves upon Corley’s et al.’s approach by 9% in MRR, and 11% in MAP, while for ST bug reports both techniques achieve comparable accuracy. JINGO demonstrates better accuracy for NL bug reports, improving MRR by 4.8% and MAP by 5.2% compared to Corley’s et al.’s. Interestingly, comparing the drop in accuracy between ST and NL bug reports, we note that JINGO lost about 3% in each metric, while Corley’s et al.’s performance decreased by about 9%. This result indicates that JINGO is in general more robust for NL bug reports, which we attribute to leveraging historical data via a translation matrix.

Overall, both techniques perform best with CR bug reports, followed with ST, and struggle the most with NL. Compared to Corley’s et al.’s approach, JINGO provides observable improvements in the CR and NL categories, but performs on par on ST bug reports.

6.5 Discussion

In this section, we detail a few salient observations resulting from evaluating our four research questions.

The evaluation of RQ1 indicates that JINGO presents an improvement over a prior technique that proposed an updatable model of the software based on changesets. More specifically, according to RQ4, the primary reason for this improvement is two fold, (1) JINGO performs better on bug reports with high number of code terms, including exact references to the methods and classes of interest, (i.e., code references); and (2) JINGO shows improvements on bug reports with high level of abstraction that do not mention any of the related code references. We believe the first reason is due to heuristics JINGO uses, such as higher weighting program element names, while the second reason is due to the two-level hierarchical architecture of JINGO. However, in the evaluation of RQ3, we observe that the accuracy of JINGO is not at the level of static (i.e., non online) approaches, in particular, those based on the vector space model.

JINGO achieves the goal of performing fast updates for newly arriving data, according to RQ2. The static VSM-based approaches we contrasted with in RQ3 are significantly faster to build than JINGO, but are 20x slower in model updating, as these models are not designed to be updatable, hence they have to be rebuilt. More specifically, VSM typically uses tf-idf to represent each document as a vector of weights, such that weight $w$ of term $t$ in document $D$ is $w_t = tf(t) \times idf(t)$. While $tf$ (term frequency), which is computed as the number of times term $t$ occurs across all documents, can be easily updated as new documents are added by modifying term counts, the same cannot be said for $idf$ (inverse document frequency). The $idf$ values depend on the number of documents in the corpus and number of times terms occur in those documents, so $idf$ values need to be re-computed as documents are added. While it is certainly the case that this can be done periodically, the VSM model does not provide for an online approach to do so.

According to our evaluation of RQ4, the most abstract (Natural Language category) bug reports still perform poorly in absolute terms, i.e., MRR=0.226 and MAP=0.143, producing weaker results than the two other categories of bug reports we identified, despite the heavy emphasis of JINGO on capturing abstract semantics via its two-layer architecture. Clearly, more work is needed to improve how bug localization techniques perform for this category of bug reports. Future research efforts should identify such bug reports explicitly as they are significantly fewer than the other categories (roughly 1/3 or 1/2 of the other categories in our randomly collected sample), while localizing them arguably provides the greatest value to end users.

6.6 Threats to Validity

The results of the study presented in this paper suffer from several threats to their validity. A key threat to the internal validity of our study are the specific parameter choices we used to build our model. Probabilistic models like ours are particularly sensitive to such parameters [Agrawal et al., 2018]. While, to mitigate this threat we employed extensive hyperparameter optimization using a separate dataset, it is clear that this threat can still be impacting our study.
Leveraging changesets for bug localization pose another threat due to possible noise that can be introduced by tangled, split, or refactoring changesets [McIntosh et al., 2011, Herzig and Zeller, 2013]. However, as long as such noisy changesets are in the minority relative to ones that reflect semantically related modifications, probabilistic techniques like LDA are likely to still produce a reasonable representation that can model how source code evolves over time [Gelman et al., 2014].

Another threat is in potential biases affecting our evaluation datasets, such as incorrect ground truth, and misclassified or already localized bug reports [Kochhar et al., 2014]. The first two biases have a potential to negatively affect the performance of JINGO as they introduce noise in the translation matrix, while the last bias can spuriously increase the results by having localization hints present. To mitigate the first threat, we followed experimental procedures used by other researchers, aiming in most cases to err on the side of caution by adopting choices that produce low false positives when identifying source code files related to a bug [Lee et al., 2018]. To mitigate the risk of using issues misclassified as bug reports, before building HCC-Repo dataset one of the authors manually inspected each project to ensure the quality of issue labeling, and identified labels referring to actual bugs. Although our efforts cannot completely remove those two biases, as observed by Kochhar et al. [Kochhar et al., 2014] they are typically not significant, hence, considering the size of our dataset, they should not have a significant effect. As for the already localized bug reports, we did not exclude them since one of our goals was to observe how bug localization performance changes for different types of bug reports. However, to present a complete picture, we included results for a manually annotated subset of bug reports with and without localization hints (Table 6).

A key threat to external validity is that we applied the bug localization technique only on a limited number of bugs, which primarily reflect popular open source Java projects. A mitigating factor is the evaluation with the large number of projects curated by the Bench4BL benchmark [Lee et al., 2018]. Additionally, this benchmark has also been applied to prior bug localization studies. Another threat to external validity is in the chosen evaluation metrics, which may not directly correspond to user satisfaction with our bug localization technique [Wang et al., 2015], impacting the generalizability and validity of the reported results. We mitigate this threat by evaluating our approach with high-quality datasets and well-known metrics, which continue to be used by academia and industry to measure the performance of IR techniques.

7 Related Work

Automatically retrieving a list of code elements based on a newly written bug report has generated significant interest among researchers for several years. In this section, we first outline the most recent and transformative approaches to IR-based bug localization, highlighting techniques that are able to adapt to rapidly changing software repositories, followed by an overview of recent evaluation techniques for bug localization.

At their core, techniques for IR-based bug localization rely on a similarity measure between a bug report and code elements in the source code base, which can be computed based on a variety of models and using different sources of information found in the bug report or the source code. For instance, BugLocator [Kim et al., 2013a] combines two rankings, one produced by similarity between the bug report and code elements using a revised Vector Space Model (rVSM) and another based on similarity of the bug report to prior fixed bug reports. BLUiR [Saha et al., 2013] improves over BugLocator by using program structure to boost specific terms (e.g., class names), while AmalGan [Wang and Lo, 2014] creates an ensemble consisting of BugLocator, BLUiR and a defect predictor leveraging development history of a project. BRTracer [Wong et al., 2014] innovates by parsing and prioritizing stack traces that may occur in bug reports. Similar to our LDA-based model for bug localization, BugScout proposes a modification of LDA that correlates bug reports and code elements via shared topics [Nguyen et al., 2011]. HyLoc uses a deep neural network to build connections between the text in bug reports and that in code elements [Lam et al., 2015], while Xiao et al. explores structural and semantic information to discover relationships between bug reports and source code [Xiao et al., 2018].

Recently, Huo et al. proposed a novel convolutional neural network to learn unified feature representation from natural and programming language that captures both lexical and program structure information [Huo et al., 2016]. This work was extended later on by modeling the sequential nature of source code using LSTM [Huo and Li, 2017]. To address the lack of historical data, Zhu et al. proposed approach based on adversarial transfer learning to detect and transfer common characteristics between projects [Zhu et al., 2020]. While most of these techniques, as ours, benefit from observing more fixed bug reports to correlate to code elements, some do not have an alternative for prediction and are likely to perform very poorly on projects with short histories. All of these techniques are built on static source code entities and not on changesets.

Researchers recognize that bug reports are diverse, and their content differences can strongly influence the effectiveness of a bug localization technique. At the same time, it has been reported that bug reports usually contain all the necessary information for effective IRBL [Mills et al., 2018]. In order to reduce the noise present in bug report and focus IRBL on
the most relevant terms, Chaparro et al. present a query reformulation strategy based on identifying sentences within a bug report that describe the observable behavior of a system [Chaparro et al., 2017], while Misoo et al. explore bug report attachments [Kim and Lee, 2019]. Rahman et al. observed that excessive program entities mentioned in the bug report may deteriorate the quality of IR-based bug localization and proposed a query reformulation technique, BLIZZARD [Rahman and Roy, 2018]. Le et al. suggests that bug localization tools can be ineffective for some bug reports and builds a model that can automatically predict the effectiveness of an IR-based bug localization tool [Le et al., 2017]. Kim et al. approach the problem similarly, by building a two-phase classifier that first determines whether the bug report has sufficient information, and, only if it does, recommends a set of code elements [Kim et al., 2013b].

Changeset-based IRBL has not yet been widely explored. There are two recent publications that have described such techniques. Locus [Wen et al., 2016] is a technique introduced by Wen et al. that both models and predicts changesets, while Corley et al. explored training on changesets and predicting code elements using Online LDA [Corley et al., 2018]. Only Corley’s technique can be classified as online, in that it does not require periodic retraining. We improve upon Corley’s work in this paper by modeling bug reports and leveraging the history of fixed bug reports. At the same time, our approach adapts to the diverse types of content present in bug reports.

While bug localization has generated significant interest among researchers, the lack of sufficiently large and standardized datasets has hindered clear comparison among the existing techniques. Recently Bench4BL has made a strong attempt to remedy this problem by providing a large dataset for bug localization [Lee et al., 2018]. Bench4BL also curates implementations of five existing bug localization techniques that can be used as baselines. While Bench4BL additionally makes several evaluation improvements, including finer-grained version matching, it is not completely precise with respect to time. Such an evaluation would reconstruct the exact snapshot of the source code when a specific bug report was introduced, instead of relying on the next release version of the software.

8 Conclusions and Future Work

In this paper, we take a significant step toward addressing the online bug localization problem, which is better suited to the rapidity and scale of modern software development than conventional release-based bug localization. We motivate the use of online bug localization based on changesets and describe previously unobserved advantages of this type of model. Our novel bug localization technique, JINGO, which is based on changesets and a dual Online LDA model, outperforms a previously reported baseline, especially when considering different types of bug reports. Future work includes studying properties of projects that makes them better suited to bug localization techniques, improving support for projects with short development histories, and leveraging preprocessing techniques that can improve noise filtering in bug reports.

References

D. Kim, Y. Tao, S. Kim, and A. Zeller. Where should we fix this bug? a two-phase recommendation model. IEEE Transactions on Soft. Eng., 39, Nov 2013a.

Ripon K. Saha, Matthew Lease, Sarfraz Khurshid, and Dewayne E. Perry. Improving bug localization using structured information retrieval. In Proceedings of the 28th IEEE/ACM International Conference on Automated Software Engineering, ASE’13, 2013.

O. Chaparro, J. M. Florez, and A. Marcus. Using observed behavior to reformulate queries during text retrieval-based bug localization. In IEEE International Conference on Software Maintenance and Evolution), Sep. 2017.

A. T. Nguyen, T. T. Nguyen, J. Al-Kofahi, H. V. Nguyen, and T. N. Nguyen. A topic-based approach for narrowing the search space of buggy files from a bug report. In 26th IEEE/ACM International Conference on Automated Software Engineering, ASE’11, 2011.

Rachel Potvin and Josh Levenberg. Why google stores billions of lines of code in a single repository. Communications of the ACM, 59, 2016.

Ranjita Bhagwan, Rahul Kumar, Chandra Sekhar Maddila, and Adithya Abraham Philip. Orca: Differential bug localization in large-scale services. In Proceedings of the 12th USENIX Conference on Operating Systems Design and Implementation, OSDI ’18, 2018.

Michael Pradel, Vijayaraghavan Murali, Rebecca Qian, Mateusz Machalica, Erik Meijer, and Satish Chandra. Scaffle: Bug localization on millions of files. In Proceedings of the 29th ACM SIGSOFT International Symposium on Software Testing and Analysis, ISSTA ’20, 2020.
Jaekwon Lee, Dongsun Kim, Tegawendé F. Bissyandé, Woosung Jung, and Yves Le Traon. Bench4bl: Reproducibility study on the performance of ir-based bug localization. In *Proceedings of the 27th ACM SIGSOFT International Symposium on Software Testing and Analysis*, ISSTA ’18, 2018.

Shivani Rao, Henry Medeiros, and Avinash Kak. An incremental update framework for efficient retrieval from software libraries for bug localization. In *2013 20th Working Conference on Reverse Engineering (WCRE)*, pages 62–71, 2013. doi [10.1109/WCRE.2013.6671281]

Ming Wen, Ronxin Wu, and Shing-Chi Cheung. Locus: Locating bugs from software changes. In *Proceedings of the 31st IEEE/ACM International Conference on Automated Software Engineering*, ASE ’16, 2016.

C. S. Corley, K. Damevski, and N. A. Kraft. Changeset-based topic modeling of software repositories. *IEEE Transactions on Software Eng.*, 2018.

Jinfeng Lin, Yalin Liu, Qingkai Zeng, Meng Jiang, and Jane Cleland-Huang. Traceability transformed: Generating more accurate links with pre-trained bert models. In 2021 *IEEE/ACM 43rd International Conference on Software Engineering (ICSE)*, pages 324–335. IEEE, 2021.

Qianqian Wang, Chris Parpin, and Alessandro Orso. Evaluating the usefulness of ir-based fault localization techniques. In *Proceedings of the 2015 International Symposium on Software Testing and Analysis*, ISSTA ’15, 2015.

Mohammad Masudur Rahman and Chanchal K Roy. Improving ir-based bug localization with context-aware query reformulation. In *Proceedings of the 2018 26th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, 2018.

Chris Mills, Esteban Parra, Jevgenija Pantiuchina, Gabriele Bavota, and Sonia Haiduc. On the relationship between bug reports and queries for text retrieval-based bug localization. *Empirical Software Engineering*, 25, 2020.

Peter Hooimeijer and Westley Weimer. Modeling bug report quality. In *Proceedings of the Twenty-second IEEE/ACM International Conference on Automated Software Engineering*, ASE ’07, 2007.

David M Blei, Andrew Y Ng, and Michael I Jordan. Latent dirichlet allocation. *Journal of Machine Learning Research*, 3(Jan), 2003.

Gemma Catolino, Fabio Palomba, Andy Zaidman, and Filomena Ferrucci. Not all bugs are the same: Understanding, characterizing, and classifying bug types. *Journal of Systems and Software*, 152, 2019.

Yuhao Zhang, Yifan Chen, Shing-Chi Cheung, Yingfei Xiong, and Lu Zhang. An empirical study on tensorflow program bugs. In *Proceedings of the 27th ACM SIGSOFT International Symposium on Software Testing and Analysis*, ISSTA ’18, 2018.

Chris Mills, Jevgenija Pantiuchina, Esteban Parra, Gabriele Bavota, and Sonia Haiduc. Are Bug Reports Enough for Text Retrieval-based Bug Localization? In *Proceedings of the 34th IEEE International Conference on Software Maintenance and Evolution (ICSM’18)*, Sep 2018.

Y. Wang, Y. Yao, H. Tong, X. Huo, M. Li, F. Xu, and J. Lu. Bug localization via supervised topic modeling. In 2018 *IEEE International Conference on Data Mining (ICDM)*, 2018.

Xuan Huo and Ming Li. Enhancing the unified features to locate buggy files by exploiting the sequential nature of source code. In *Proceedings of the 26th International Joint Conference on Artificial Intelligence*, 2017.

Yan Xiao, Jacky Keung, Qing Mi, and Kwabena E. Bennin. Bug localization with semantic and structural features using convolutional neural network and cascade forest. In *Proceedings of the 22nd International Conference on Evaluation and Assessment in Software Engineering*, 2018.

Stacy K. Lukins, Nicholas A. Kraft, and Letha H. Etzkorn. Bug localization using latent dirichlet allocation. *Inf. Softw. Technol.*, 52, Sep 2010.

Matthew Hoffman, Francis R Bach, and David M Blei. Online learning for latent dirichlet allocation. In *Advances in Neural Information Processing Sys.*, 2010.

A. Alali, H. Kagdi, and J. I. Maletic. What’s a typical commit? a characterization of open source software repositories. In *Proceedings of the 16th IEEE International Conference on Program Comprehension*, 2008.

Ahmed E Hassan and Richard C Holt. Predicting change propagation in software systems. In *Proceedings of the 2004 20th IEEE International Conference on Software Maintenance*, 2004.

Atif Memon, Zebao Gao, Bao Nguyen, Sanjeev Dhanda, Eric Nickell, Rob Siemborski, and John Micco. Taming google-scale continuous testing. In *Proceedings of the 39th International Conference on Software Engineering*, ICSE ’17, 2017.

T. L. Graves, A. F. Karr, J. S. Marron, and H. Siy. Predicting fault incidence using software change history. *IEEE Transactions on Soft. Eng.*, 26, 2000.
S. Amasaki, H. Aman, and T. Yokogawa. On the effects of file-level information on method-level bug localization. In *46th Euromicro Conference on Software Engineering and Advanced Applications*, SEAA ’20, 2020.

Brian Eddy, Nicholas Kraft, and Jeff Gray. Impact of structural weighting on a latent dirichlet allocation-based feature location technique. *Journal of Software: Evolution and Process*, 30, Sep 2017.

Yu Wang, Eugene Agichtein, and Michele Benzi. Tm-lda: Efficient online modeling of latent topic transitions in social media. In *Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD ’12, 2012.

Xin Ye, Razvan Bunescu, and Chang Liu. Learning to rank relevant files for bug reports using domain knowledge. In *Proceedings of the 22Nd ACM SIGSOFT International Symposium on Foundations of Software Engineering*, FSE ’14, 2014.

Yaojing Wang, Yuan Yao, Hanghang Tong, Xuan Huo, Ming Li, Feng Xu, and Jian Lu. Enhancing supervised bug localization with metadata and stack-trace. *Knowledge and Information Systems*, 2020.

Bader Alkhazi, Andrew DiStasi, Wajdi Aljedaani, Hussein Alrubaye, Xin Ye, and Mohamed Wiem Mkaouer. Learning to rank developers for bug report assignment. *Applied Soft Computing*, 95, 2020.

Chu-Pan Wong, Yingfei Xiong, Hongyu Zhang, Dan Hao, Lu Zhang, and Hong Mei. Boosting bug-report-oriented fault localization with segmentation and stack-trace analysis. In *Proceedings of the IEEE International Conference on Software Maintenance and Evolution*, ICSME ’14, 2014.

Amritanshu Agrawal, Wei Fu, and Tim Menzies. What is wrong with topic modeling? and how to fix it using search-based software engineering. *Information and Software Technology*, 98, 2018.

Christoph Treude and Markus Wagner. Predicting good configurations for github and stack overflow topic models. In *Proceedings of the 16th International Conference on Mining Software Repositories*, MSR ’19, 2019.

David Binkley, Daniel Heinz, Dawn Lawrie, and Justin Overfelt. Understanding lda in source code analysis. In *Proceedings of the 22nd International Conference on Program Comprehension*, ICPC ’14, 2014.

Sergei Koltcov, Olessia Koltsova, and Sergey Nikolenko. Latent dirichlet allocation: stability and applications to studies of user-generated content. In *Proceedings of the 2014 ACM Conference on Web science*, 2014.

J. Romano, J.D. Kromrey, J. Coraggio, and J. Skowronek. Appropriate statistics for ordinal level data: Should we really be using t-test and Cohen’sd for evaluating group differences on the NSSE and other surveys? In *annual meeting of the Florida Association of Institutional Research*, 2006.

Klaus Changsun Youn, June Ahn, Jeongho Kim, and Eunseok Lee. Bug localization based on code change histories and bug reports. In *2015 Asia-Pacific Software Engineering Conference (APSEC)*, pages 190–197, 2015. doi:10.1109/APSEC.2015.23.

Shivani Rao and Avinash Kak. Retrieval from software libraries for bug localization: A comparative study of generic and composite text models. In *Proceedings of the 8th Working Conference on Mining Software Repositories*, page 43–52, 2011.

Shane McIntosh, Bram Adams, Thanh H.D. Nguyen, Yasutaka Kamei, and Ahmed E. Hassan. An empirical study of build maintenance effort. In *Proceedings of the 33rd International Conference on Software Engineering*, ICSE ’11, 2011.

Kim Herzig and Andreas Zeller. The impact of tangled code changes. In *Proceedings of the 10th Working Conference on Mining Software Repositories*, MSR ’13, 2013.

Andrew Gelman, John B Carlin, Hal S Stern, David B Dunson, Aki Vehtari, and Donald B Rubin. *Bayesian Data Analysis*, volume 2. CRC Press, 2014.

Pavneet Singh Kochhar, Yuan Tian, and David Lo. Potential biases in bug localization: Do they matter? In *Proceedings of the 29th ACM/IEEE International Conference on Automated Software Engineering*, ASE ’14, 2014.

Shaowei Wang and David Lo. Version history, similar report, and structure: Putting them together for improved bug localization. In *Proceedings of the 22Nd International Conference on Program Comprehension*, 2014.

A. N. Lam, A. T. Nguyen, H. A. Nguyen, and T. N. Nguyen. Combining deep learning with information retrieval to localize buggy files for bug reports. In *30th IEEE/ACM International Conference on Automated Software Engineering*, ASE ’15, Nov 2015.

Xuan Huo, Ming Li, and Zhi-Hua Zhou. Learning unified features from natural and programming languages for locating buggy source code. In *25th International Joint Conference on Artificial Intelligence*, 2016.

Ziye Zhu, Yun Li, Hanghang Tong, and Yu Wang. Cooba: Cross-project bug localization via adversarial transfer learning. In *Proceedings of the 29th International Joint Conference on Artificial Intelligence*, IJCAI, 2020.
Misoo Kim and Eunseok Lee. A novel approach to automatic query reformulation for ir-based bug localization. In *Proceedings of the 34th ACM/SIGAPP Symposium on Applied Computing*, SAC ’19, 2019.

Tien-Duy B. Le, Ferdian Thung, and David Lo. Will this localization tool be effective for this bug? mitigating the impact of unreliability of information retrieval based bug localization tools. *Empirical Softw. Engg.*, 22, Aug 2017.

D. Kim, Y. Tao, S. Kim, and A. Zeller. Where should we fix this bug? A two-phase recommendation model. *IEEE Transactions on Soft. Eng.*, 39, Nov 2013b.