Issue Link Label Recovery and Prediction for Open Source Software

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Abstract—Modern open source software development heavily relies on the issue tracking systems to manage their feature requests, bug reports, tasks, and other similar artifacts. Together, those “issues” form a complex network with links to each other. The heterogeneous character of issues inherently results in varied link types and therefore poses a great challenge for users to create and maintain the label of the link manually. The goal of most existing automated issue link construction techniques ceases with only examining the existence of links between issues. In this work, we focus on the next important question of whether we can assess the type of issue link automatically through a data-driven method. We analyze the links between issues and their labels used the issue tracking system for 66 open source projects. Using three projects, we demonstrate promising results when using supervised machine learning classification for the task of link label recovery with careful model selection and tuning, achieving F1 scores of between 0.56-0.70 for the three studied projects. Further, the performance of our method for future link label prediction is convincing when there is sufficient historical data. Our work signifies the first step in systematically manage and maintain issue links faced in practice.

I. INTRODUCTION

Issue tracking systems (ITSs) play an increasingly important role in modern open source software development as a central location for submitting and managing software issues. An issue in this context often represents a piece of information about the current system or a unit of work to be completed to improve the software product. This could be a requested feature, a reported bug, a planned task, missing documentation, etc. In practice, depending on the complexity of software projects and how the projects are managed, meaningful associations often form among issues, referred to as horizontal trace links [20]. Figure 1 exemplifies the local connections of one issue from one of the open source projects in our case study HIVE using Atlassian Jira. This feature request is linked to two other features, one sub-task, and one bug.

The heterogeneous nature of the content of the issues in the ITSs leads to substantial variance in the types of the trace links between issues. To record the specific type for links, Jira allows the developer to assign particular labels as metadata of the links. In Figure 1, the issue HIVE-17432 was linked with other issues using three distinct labels, i.e. contains, is blocked by, is duplicated by. Software stakeholders rely on this information to identify all the tightly related issues and their particular relationships to perform different tasks such as prioritizing the new features, understanding the current status of development, communicating the progress towards completing certain goals [3], [11], just to name a few.

Making use of the link label functionality in the ITSs requires additional effort to create and maintain these labels [33]. Currently, project stakeholders can only assign and update the labels manually. Given that the experience and preference of the stakeholders vary considerably in open source projects, the same link labels might be used inconsistently within and across projects. Moreover, when the issues evolve over time, extra work is devoted to reevaluate the link labels or they will become outdated or unreliable. Therefore, automated support for suggesting and updating the link labels is a non-negligible step for enhancing the current ITSs to achieve effective issue navigation [42] and reasoning [25].

In this work, we take on the task of automated recovery and prediction of labels for horizontal trace links in the ITSs. Link label recovery refers to the scenario of inferring link labels for issues that have already been in the ITS, while Issue link label prediction refers to predicting link labels for future (i.e. unseen) issues. By using the existing trace link labels and machine learning techniques, we establish a method for recovering and predicting trace link labels that can adapt to the nuances of different software projects. Furthermore, we incorporate knowledge external to improve the learning of
trace link labels. The performance of our methods is evaluated in two different scenarios to simulate the context of link label recovery and prediction in practice, respectively. In particular, we address the following key research questions:

**RQ1**: What are the characteristics of labels used for issue links in open source projects?

**RQ2**: To what extent can we recover link labels using machine learning techniques combining the textual content of issues, textual content external to the ITS and the context information about the issues and issue links?

**RQ3**: To what extent can we recommend the labels for future links giving the historical link labels in the project?

We observe that the link labels are heavily used in the ITSs for trace links between issues. Our method can effectively recover link labels in the ITS for various sized projects. Given a sufficient amount of training data, our method can further predict labels for future links. The contribution of this work is two-fold. First, our work complements the existing research on horizontal traceability that mainly focused on constructing trace links without considering the particular types of links. Second, we propose a novel link label recovery and prediction solution that can reasonably fit into the state-of-the-art ITSs.

## II. RELATED WORK

### A. Software Traceability

Previous work on software traceability has ranged from recovering and analyzing, to interpreting and making use of artifact connections. Several recent efforts has focused on analyzing the connections between various artifacts written informally in terms of language use, including code reviews [21], question and answer [15] and bug reports [22], among others. Our work is closer to this line of work. Rather than choosing one particular link or artifact type, we focus on the breadth of link types frequently used in ITS.

Researchers and practitioners have additionally investigated the use of trace links to support a wide variety of development and maintenance tasks such as release planning [12], impact analysis [14], completion analysis, source-code justification analysis [37], test result and fault tracing [40] and compliance verification [27]. The link label recovery and prediction solution proposed in this work can be used as a precursor to any of the above tasks that rely on certain types of links.

### B. Automated Trace Link Construction

Given the magnitude of the traceability problem, there has been much previous work on automated and semi-automated solutions to trace link creation and maintenance [1], [16], [19]. The majority of this work deploys information retrieval or machine learning techniques but does not handle suggesting link types during trace link creation. There has also been work on heuristic-based trace link creation methods [17], [39]. In particular, the links can be grouped into different categories based on which heuristic has been applied to create the link [39]. Instead of a heuristic-focused approach, we investigate automated solutions to the problem of trace link label recovery and prediction for the ITS in which the historical labels can be mined and used for training the machine learning models.

### C. Trace links in Issue Tracking Systems

ITSs resemble change requests or just-in-time requirements that are triaged and addressed by team members continually [13]. As a result, traceability for ITSs has attracted some attention in recent literature [33], [42]. The relationship between on particular issue has been investigated in previous work. For example, Maalej, et. al studied the links between tasks [26] for the purpose of work planning. Tasks, however, only represent a marginal segment of a project’s software artifacts (see Section III). Similarly, different link types have been considered between question and answer [15] and bug reports [22]. Our initial observation reveals that the horizontal links between issues are often across issue types (e.g. see Figure 1). Therefore, we expand the scope of link types across software issues that represent a rich set of artifact types such as bug reports, feature requests, improvements, etc.

### D. Issue Trace Link Types

In the context of investigating link labels used for open source projects, our work is closely related to the recent studies by Tomova et. al. [42] and Nicholson et. al [36]. Tomova et. al presented preliminary results on recovering link labels on seven OSS projects using Jira [42]. They focused on four default link labels provided by Jira and discussed the impact of selecting threshold when using a term matching based method. Their observation demonstrates the ineffective for retrieving links with the type of “relates to” and calls for closer investigation on link label usage in OSS and tool support. Nicholson et. al. provided a more comprehensive picture of how the link labels were used across 66 OSS projects using Jira [42]. Their study reveals that the customized link labels are commonly used, and can appear more frequently than the default label of “is clone of”. They also demonstrated that the network structure formed by historical links and their labels can be useful to extract patterns to recover missing links and corresponding labels. The dependency of one particular network structure, however, limits the applicability of such a method on predicting the label of a wide set of links.

## III. ISSUE LINK CHARACTERISTICS AND DATASET CREATION

In this section, we perform a series of empirical investigations to understand the explicit links that project stakeholders assign between issues (RQ1). We further describe the steps that we have taken to prepare the selected project datasets for the experiments of automated link label recovery (in Section V) and prediction (in Section VI).

### A. Issue Links and Their Labels for Apache Projects

Our study is based on a dataset created by Nicholson et. al. for their empirical study of Jira issue networks [32], [33]. The complete dataset was mined from the sixty-six Apache Open Source projects and contains a total of 71,087 trace links.
Fig. 2: Distribution histogram of the ratio of linked issues to total issues in 66 Apache projects [32]. The location of the case study projects is indicated by the vertical lines.

between 90,936 issues. To the best of our knowledge, this is the largest dataset on horizontal trace links. It also contains a rich set of metadata including the link labels that represent the particular types specified by issue creators or maintainers.

As shown in Figure 1, Jira allows users to assign distinct labels to issue links to indicate different types of links. Jira provides four default labels: relates to / relates to, duplicates / is duplicated by, blocks / is blocked by and clones / is cloned by. Authorized project stakeholders can also create and customize new labels to express additional associations between issues according to their needs. The labels saved in the ITS serve as a lens through which we can examine the issue link types on a large scale. Note that although Jira permits linking issues across different projects, in this work, we only focus on within-project links that constitute a sizable portion of the links in the ITSs.

We first examine how prevalent the issues contain horizontal trace links in each project. To achieve this, we calculate the ratio of issues that have at least one link to the total number of issues in that project. Figure 2 shows the histogram of this ratio across all projects. On average, more than 18% of issues in a project have links to other issues with a standard deviation of 10%. In terms of the link labels used in practice, previous work dataset suggests that the distribution of the occurrence of different labels is highly skewed [33] – among 16 unique link labels, related to label accounts for nearly half of the links (45.56%). Furthermore, a non-trivial portion of link label categories falls below the 1% of the trace links.

B. Project Case Studies and Dataset Creation

To further investigate the link labels used in practice and the potential of using machine learning techniques to alleviate the manual effort, we focus on three projects from this dataset for the remaining study, i.e. Hive, Ambari, and Flex. This selection is based on the following important reasons: First, all three projects are actively being developed and maintained. Second, they represent projects with different characteristics in terms of issue traceability (see Figure 2). Third, they have active CWiki pages which are the project-specific wiks managed by the project community. CWiki pages contain supplementary project information such as release notes, documentation and discussions which enable us to incorporate additional project specific data during link label recovery (further discussed in Section IV-B). Among all the 66 projects we have examined, these three projects are the only ones that we can obtain such project documentation with reasonable effort.

The breakdown of issue types that contain links in each studied project is summarized in Table I. We also present the link labels with their respective quantities in Table II. For less than 10.17% of the total links are between bugs and tasks, the issue type of improvement also frequently contains links to other issues, ranging between 10.45% to 17.61%. Furthermore, we observe that 14.17% - 33.85% of the total links are between bug and non-bug issues. This big portion of links has been omitted from the previous work that only focuses on links between one issue types [45]. Additionally, the overlapping between the less frequent labels with the more dominant ones is also observed in these datasets, such as dependent and depends upon, Blocked and blocks. These overlapping might pose risk to the quality of the dataset. To reduce such a potential threat to the validity of our study, we exclude the link labels if their occurrences account for less than 1% of the total links in that project and if the occurrences are less than 20 in our link semantic solution.

When creating the dataset for the remaining study, i.e. automated link label recovery and prediction, we retrieve issue summaries, descriptions, types, resolution status, linked issues, as well as link labels. Among them, summary contains a brief outline of the issue while the description details the technicalities of the issue such as the reproduction steps in the case of a bug, or the detailed requirements in the case of a feature request. In our dataset, the summary lengths range from an average of 57 characters in Hive to 65 characters in Flex. Descriptions are, as anticipated, more detailed, containing an
Recall that the summary and description of issues contain information with different granularity. To retain this distinction while capturing the textual content of each project, summaries and descriptions are treated as separate documents when fitting the TF-IDF model. The resulting issue vector then is the concatenation of the vector representation of its summary and description which produces a vector of size $2 \times N$ where $N$ is the vocabulary size of the project. Each link is then encoded as a fixed-sized feature vector concatenating the TF-IDF representation of two issues in question. The textual features generated this way is denoted by $textEnc_{t, idf}$.

### B. Text Encoding Integrating External Resources

Depending on the granularity of the issues and the terminology used by the issue authors, the gap of the textual content between two linked issues can be significantly large [18]. This gap can be potentially filled with information about the language usage, the application domain, and the project itself. To consolidate different kinds of information for link labels related tasks, we investigate alternative text encoding functions with word embedding techniques. Different from the TF-IDF model, word embedding refers to the process of transforming continuous vector representations of words from a high-dimensional space to one with much fewer dimensions [29]. It can capture several important syntactic and semantic properties of the words when trained to build a language model using a large collection of documents [24]. Using word embeddings as input has been shown to greatly improve performance in many natural language processing related tasks such as image captioning [23] and sentiment analysis [31]. In the context of software requirement analysis, it also has been applied tasks such as identification of ambiguous cross-domain terms [30].

We primarily take advantage of the large amount of online text about general concepts, software development and specific open source projects to pre-train the word embeddings to capture the distribution of word usage in different corpus. The word embeddings can then be updated to fit the issue text for each project. Particularly, the following resources are used in our study, with an increasing level of relevance to the domain:

- **Wikipedia (Wiki):** We use the wikitext103 dataset [28] which consists of verified Wikipedia articles with a total of over 103 million words in size. Previous work has demonstrated that word embeddings trained on this dataset can effectively capture the statistical distribution of general terms.
- **Stack Overflow (SO):** We use the StackSample dataset which contained 10% of Stack Overflow questions and answers as of 2016. We include this dataset because the previous study has suggested that software-specific documents might be more effective than general-purpose corpus to capture word similarities for tasks that rely on processing software artifacts [41].
- **Project Documentation (PD):** Cwiki pages of each project in our case study contain the information such as docu-

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### A. Text Encoding using Issue Content

Textual features are heavily used in the literature to assess the existence of trace link [18], [20]. Term Frequency-Inverse Document Frequency (TF-IDF) model, one of the most common ways to make decisions on document relevancy, serves as a strong baseline when analyzing issue content [3], [44]. Intuitively, TF-IDF model capture how important a word is to each document in a collection of documents. We use the Scikit-Learn library [35] to transfer each pre-processed text into the vector representation.

### TABLE II: Link labels and their occurrence in project AMBARI, FLEX, and HIVE respectively, with more than 10% are highlighted. Note, the labels with percentage < 1% or occurrence < 20 are excluded from our case study for that project.

| Link Label | AMBARI | FLEX | HIVE |
|------------|--------|------|------|
| relates to | 310 / 32.91% | 94 / 38.06% | 3060 / 52.66% |
| duplicates | 305 / 32.38% | 51 / 20.65% | 708 / 12.18% |
| depends upon | 70 / 7.43% | 13 / 5.26% | 373 / 6.42% |
| requires | 38 / 4.03% | 20 / 8.10% | 134 / 2.31% |
| contains | 27 / 2.87% | 23 / 0.81% | 103 / 1.77% |
| is a clone of | 27 / 2.87% | 23 / 9.31% | 71 / 1.22% |
| breaks | 26 / 2.76% | 14 / 5.67% | 190 / 3.27% |
| incorporates | 21 / 2.23% | 8 / 3.24% | 339 / 5.83% |
| supercedes | 15 / 1.60% | 2 / 0.81% | 84 / 1.45% |
| causes | 6 / 0.64% | 0 / 0.0% | 11 / 0.19% |
| Blocked | 5 / 0.53% | 0 / 0.0% | 10 / 0.17% |
| is a parent of | 2 / 0.21% | 0 / 0.0% | 3 / 0.05% |
| Dependent | 1 / 0.11% | 0 / 0.0% | 5 / 0.09% |
| Dependency | 0 / 0.0% | 0 / 0.0% | 1 / 0.02% |
| Parent Feature | 0 / 0.0% | 0 / 0.0% | 1 / 0.02% |

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average of from 863 characters in Ambari to 1059 characters in Flex.

When creating the dataset for model training and testing, we follow a standard text pre-processing method to normalize both the issue summary and description: we first remove known words, we then convert them to their standard lemma form. Additionally, camel-cased tokens are split into separate tokens using regular expressions and also converted to lowercase and their standard lemma form. When creating the dataset for model training and testing, we use the concatenation of the vector representation of its summary and description which produces a vector of size $2 \times N$ where $N$ is the vocabulary size of the project. Each link is then encoded as a fixed-sized feature vector concatenating the TF-IDF representation of two issues in question. Textual features generated this way is denoted by $textEnc_{t, idf}$.

### IV. ISSUE Link REPRESENTATION

In this section, we seek to represent the issue links for recovering and predicting their labels in practice using machine learning techniques. We first discuss how we extract the textual features from the issue content. We then extend the textual features to incorporate additional resources external to the ITS. Finally, we use the metadata of issues to capture the context in the ITS. We use concatenated feature sets as input to recover and predict link labels in the next two sections.

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| Dependent | 1 / 0.11% | 0 / 0.0% | 5 / 0.09% |
| Dependency | 0 / 0.0% | 0 / 0.0% | 1 / 0.02% |
| Parent Feature | 0 / 0.0% | 0 / 0.0% | 1 / 0.02% |
mentation, release notes, announcements, reference guides, and frequently asked questions. These were mined using the selenium webdriver too\(^8\). We aim to explore the potential of capturing project specific context for link label recovery through word embedding techniques. We mined a total of 247 pages from the Ambari project, 327 from the Flex project and 57 from the Hive project.

We represent each word in the dataset vocabulary as a fixed-sized dimensional fastText embedding \([7]\). The fastText embedding type was chosen because it additionally accounts for the co-occurrence of sub-word tokens (i.e., groups of characters), and introduces various optimizations for training speed. To aggregate a document’s word vectors we average the word embedding vectors, which is a technique known as a Bag of Vectors \([10]\).

Once we have used the document collections above to train a set of word embeddings \({\{\text{wiki}, \text{stack}, \text{proj}\}}\), we update the embeddings by training using the same objective on entire issue text (summaries and descriptions) from the respective project. The word embedding text encoding techniques pre-trained by Wikipedia, Stack Overflow, and project documentation are denoted by \text{textEnc}_{\text{wiki}}, \text{textEnc}_{\text{stack}} and \text{textEnc}_{\text{proj}} respectively.

### C. Issue Metadata

Metadata from the ITSs has proven to be useful to suggest trace links between commit message and issue post \([36]\). We hypothesize that the reason for assigning certain link labels is also correlated with the contextual information that can be extracted through the issue metadata. An example of one typical issue from Jira is given in Figure 1. In particular, we include the following metadata when encoding the issue links:

- \text{timeDelta}(\text{issue}_1, \text{issue}_2): The normalize difference between the creation time (in days) of \text{issue}_1, and \text{issue}_2 respectively;
- \text{type}(\text{issue}): The issue type (see Table I);
- \text{assignee}(\text{issue}): The unique identifier of the issue assignee. An special identifier is used for no assignee.
- \text{reporter}(\text{issue}): The unique identifier of the issue reporter.

This metadata is then transformed into a feature-set. The categorical metadata items such as type, assignee, and reporter are all represented as \(N\)-dimensional one-hot vectors, where \(N\) is the number of categories, that contains 0 in all indexes except the index corresponding to the category in question which contains 1.

### V. AUTOMATED TRACE LINK LABEL RECOVERY

Automated issue trace link solutions aims to assist the tasks such as the recovery of missing link labels and link label maintenance. Given a certain amount of labels provided by the project stakeholders, such solutions improve the quality of the remaining labels between issues saved in the ITS. This process can serve to support project management as well as other retrieval based tasks. Towards this end, we can build statistical classifiers that learn from the important features of the existing link labels and suggest the labels for other links under consideration. We depict the complete process of our method in Figure 3.

#### A. Supervised Machine Learning Classification

In this work we experiment with the following supervised machine learning models due to their wide adoption in text mining tasks \([48]\) and the improved results reported in recent work on software artifacts \([8], [38]\)

- \text{Logistic Regression (LR)}: A parametric model which fits parameters to minimize the cross-entropy between the model predictions and the output. This model assumes that the output is a linear function of the parameters and the input.
- \text{Random Forest (RF)}: A weighted average (ensemble) of multiple Decision Tree classifiers \([8]\). Each decision tree is a non-parametric model based on a series of if-then statements.
- \text{Neural Network (NN)}: A parametric model trained using the backpropagation algorithm \([43]\) to minimize a loss function such as cross entropy in the case of classification. The input is passed through a series of weighted linear transforms (similar to Logistic Regression) and non-linear functions such as the hyperbolic tangent or sigmoid function.

While there have been advances observed using more complex neural network models to encode software artifacts \([16], [46]\), we exclude them from this work because of the constraints posed by our dataset. Primarily, the highly imbalanced dataset contains many categories that only have a small number of instances (see Table I) that are insufficient to train more powerful models without over-fitting.

#### B. Model Hyper-parameter Tuning

Table I summarizes the chosen hyper-parameters that are relevant to the classifiers and their values to tune. While this list of hyper-parameters is not exhaustive, preliminary experiments showed this subset to have the greatest effect on overall performance. To balance the cost and potential benefit of tuning, we use a random search strategy to sample a value for each hyper-parameter for a fixed number of iterations \([5]\). Additionally, to contend with the large imbalances between link labels discussed in Section III-A, we experiment with the SMOTE \([9]\) algorithm to create synthetic data samples based on the distribution of nearest neighbors for each

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\(^8\)https://www.seleniumhq.org/projects/webdriver/
TABLE III: The definition of hyperparameter and the values in the search space. Defaults shown in bold. In the keys, SM = SMOTE, LR = Logistic Regression, RF = random Forest, NN = Neural Network.

| HyperPara. | Definition                                                                 | Values                                                                 |
|------------|---------------------------------------------------------------------------|------------------------------------------------------------------------|
| SM_k       | The k nearest neighbours to create synthetic SMOTE examples.              | {1, 2, 3, 4, 5, 6, 7}                                                  |
| LR_c       | Inverse L2 regularization strength: (α^{−1}).                              | {10, 100, 1000}                                                        |
| RF_e       | The number of decision tree estimators.                                    | {log(10), [encoding], √[encoding]}                                     |
| RF_f       | The function which determines the max. number of features when adding branches. | {−4, −3, −2, −1}                                                      |
| NN_a       | L2 Regularization strength α                                               | {0.1, 0.25, 0.5}                                                       |
| NN_drop    | The dropout probability in the hidden layer.                               | {25, 50, 75, 100, 125}                                                 |
| NN_e       | The number of training epochs.                                            | {10^{−3}, 2, −1, 0}                                                    |
| NN_lr      | The learning rate used to update the parameters.                          |                                                                       |

existing data point. The parameters of SMOTE are also tuned based on recommendations in related work [2].

C. Experiment Design

We implement the complete link label recovery solution using Python 3.7, Scikit-learn [35] and Pytorch [34]. This solution can be configured with several variations, including choosing the feature-set to encode the links (text features, issue metadata, or both) and the model to perform the actual learning and classification (i.e. LR, RF, or NN). To properly evaluate the performance of our proposed solution on the link label recovery task, we use the cross-validation technique to assess the model performance on the dataset generated in Section III-B. This experiment aims to answer RQ2, i.e. to what extent can we recover link labels using machine learning techniques combining the textual content of issues, textual content external to the ITS and the context information about the issues and issue links.

Specifically, we perform 5-fold stratified cross validation to maintain the distribution of the link labels in both the training and testing set. Each time, four folds of data are used for training the model while the remaining one fold is used for testing. During model training, we further split the training data to perform hyper-parameter tuning. On Logistic Regression and Random Forest classifiers, we use 5-fold cross-validation on the training data to find the optimal configurations from the search space in Table III. For the neural network, because of the high training cost, we use 25% of the available training data as a validation set to choose the values for hyper-parameters.

On the testing data, we use the model output to calculate the F1 measures for each link label. F1 is interpreted as the harmonic mean of the precision and recall, where precision details how many predictions were correct and recall measures how much of the true labels were preserved by the classifier’s output. Since the number of instances for different link labels are highly imbalanced, we weigh the F1 measure by the frequency of label occurrences when aggregating the result across all labels. Such process is repeated five times until all the instances in the dataset are tested once. The performance of the model are then averaged among all five folds.

To benchmark the label recovery performance, we consider two baselines. The first one is a majority classifier which predicts the most common class regardless of the input, also known as a ZeroR classifier. It is useful to serve as a baseline to assess whether more complex classifiers have learned useful features or have over-fit the training data [21]. The second baseline is using the three classifiers without hyper-parameter tuning. Instead, we use the default values corresponding to the values suggested by the implementing library (entries in bold in Table III). In addition, we compare the performance of the classifiers with and without SMOTE.

D. Experiment Results

1) Effect of issue link representation: Figure 4 depicts the F1 scores obtained using different link representations. The variance for each link representation comes from the use of SMOTE and the selection of the classifier. The variance is relatively small when using the TF-IDF model to encode the text content of the issues. When using external resources, however, the variance generally increases drastically. Integrating the external resources through word embedding did not improve the performance on the link label recovery task compared to using the simpler, TF-IDF model. The benefit of using metadata, on the other hand, is apparent. All the link representations show increased performance when including additional metadata. The best configuration of link representation is using TFIDF + meta information: the median of weighted F1 measure is 0.54 in Ambardi, 0.65 in Flex and 0.58 in Hive.

2) Effect of handling imbalance classes: We decompose the results of using the best link representations from the previous observations. Table IV compares the performance of our method when SMOTE is turned off versus when SMOTE turned on and its parameter is included during model tuning. All the best performance excels ZeroR largely. The effect of having SMOTE, however, varies widely. While SMOTE reduced the performance of the NN model, we observe only a modest change for LR and RF. One potential explanation is that the feature representation used in this experiment is very high-dimensional. Previous work has shown that oversampling high dimensional data is problematic for some machine learning classifiers [6]. We leave rigorous investigation on the cause of the limited or even negative effect of using SMOTE to our future work.

3) Effect of projects: The best models in our method achieved a weighted F1 score of 0.56 in Ambardi, 0.70 in Flex, and 0.61 in Hive. Comparing the three projects with various configurations, Hive and Ambari showed much less
variance than Flex. This may be explained by the disparity among the size of the dataset. The stability of machine learning techniques depends greatly on the quality and quantity of available training data. Due to the small size of Flex, minute perturbations caused by the randomization process might lead to varied classification results for each label. In such a case, both correct and incorrect classifications on a single label will affect the F1 measure to a greater extent.

VI. Predicting Future Link Labels

In the previous sections, we attempted to model the task of recovering missing links given the entirety of the project context. Another common scenario, however, is predicting future links given a model trained using past links. This scenario cannot be evaluated using stratified cross-validation because the future links and their labels are not available during the model training. We can, however, gain a more accurate picture of prediction performance by varying the training and testing dates. In this section, we investigate the extent to which predicting future link labels can be accomplished by our automated solution (our RQ3).

A. Experiment Design

The complete traceability solution in the prediction setting will involve creating the links first. This can be done either manually by the stakeholders manually or by relying on the vast amount of previous work on automated traceability [16], [20]. Therefore, the evaluation of this preceding step is out of the scope of this work. We focus instead on evaluating the performance of the next step, predicting the labels when the links are being created. While the models themselves won’t be changed from the recovery setting, the performance of the models may vary greatly. Firstly, in the prediction case, the model may encounter word tokens it has never seen during training, known as an Out of Vocabulary (OOV) issue. This can be handled in a number of different ways such as selectively updating the model [4], or simply ignoring the new value. In this work for the sake of simplicity, we replace out of vocabulary word tokens by a dummy value that will not change the issue’s characterization. Secondly, the distribution of the

Figure 5 shows the confusion matrix of test predictions using the best performing model on each dataset. For project Ambari and Flex, links with various labels can be easily misclassified as relates to and duplicates. The big number of instances of these two classes in the training set might be the culprit and using SMOTE in Ambari is not particularly effective. In Hive, the classifier is also having difficulty to differentiate relates to with other labels. It might also be caused by the lack of a clear definition of the link labels when using the relates to label. The links might exhibit heterogeneous features. On the other hand, for some labels, such as depends upon, incorporates and requires, the best models are very effective, achieving an highest F1 score of between 0.69 and 0.88. Such encouraging results indicate the potential of learning accurate link labels to support specific tasks such as feature dependency analysis and work planning.

In summary, the performance of the current link label recovery solution is promising, yet not perfect, especially for the labels with limited instances during training. As a first step, it provides useful information to mitigate the effort of assigning link labels from scratch. The output of the method can suggest link labels in a way that resembles past usage. Such support can also potentially reduce the inconsistency when manually assigning labels.
training data and the testing data might differ depending on the phase in which the project is situated. To capture various adaptations of this scenario, we split the training and testing data in two ways based on the time of issue creation.

We first find the date at which 60% of the issues in the project were created. From those issues, we create a training set of links only between these issues. The model tuning and training are performed on this training set. When we prepare the word embeddings, we also use this set to update the embeddings as discussed in Section IV to prevent information about future issues “leaking” into the training process. The next 20% of issues are used to create the test set, i.e., links from these new issues to the complete set of issues. We denote this setting as 60 – 20. This process is then repeated using the 80% date issues as the training set and the last 20% data issues as the testing set for comparison, denoted by 80 – 20. Such a division of training and testing data in two settings aims to make a fair comparison of the performance on test sets. Similar to Section V-C, we perform the hyper-parameter tuning on the classifiers and use the F1 measure for each link label on the held-out future test set.

### B. Experiment Result

As shown in Table V, the best models achieved a weighted F1 score of 0.326 in Ambari in the setting of 60 – 20, 0.570 in Flex, and 0.333 in Hive from the same setting. Compare to the best result achieved in the recovery scenario (0.56 in Ambari, 0.70 in Flex, and 0.61 in Hive), such amount of deterioration can reasonable considering the smaller amount of training data, the out-of-vocabulary issue and label distribution shift as we discussed earlier. However, when the model is trained in the later stage of the project, the performance of the model can improve greatly, ranging between 18% to 42%.

We breakdown the performance for each label from the test set in Figure 6. The performance of our method varies for different labels, similar to the trend observed in the label recovery task. The missing bar indicates no prediction on that label. Comparing the setting of 60 – 20 and 80 – 20, the performance of most labels has demonstrated improvement. The exceptions are requires in Flex, and several other labels in Flex and Hive. The first case happens because requires has not shown in the testing data of 80 – 20 so that we cannot estimate our model on such instances. We zoomed in the other cases and found the configuration of the best model changes from using Wiki Embedding to the TFIDF model for Hive when the training data increase from 60% to 80%. Because we perform hyper-parameter tuning during training, while the best configuration is performing better in general, it might misclassify a small number of instances to preserve the general trend of improvement. These results indicate that while our solution can perform reasonably well in prediction scenarios, especially when the historical data accumulate, human inspection is still necessary to ensure the high quality of the suggested link labels.

### VII. Threats to Validity

**Internal Validity**: Automated solutions including machine learning often require making a number of related decisions in order to optimize performance. These decisions can include the type of classifier and the subsequent set of hyper-parameters and their values, the feature representation of input values, the

| Ambari | Flex | Hive |
|--------|------|------|
| 60 – 20 | 0.326 | 0.570 | 0.333 |
| 80 – 20 | 0.416 | 0.669 | 0.416 |

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**TABLE V**: Weighted F1 when predicting future link labels in two time-based evaluation settings, 60 – 20 and 80 – 20.
evaluation criteria and metrics, and the optimization methods. Evaluating every possible combination of these decisions is at best resource intensive. In this work, we have presented experimental results on a subset of these potential choices based on prevalence in previous work as well as preliminary empirical experimentation. Through careful consideration of issues such as hyper-parameter tuning, handling unbalanced classes, and treating time-sensitive attributes, our study carries direct implications when applying learning-based methods on practical link labeling problems.

External Validity: The datasets used in this work primarily focused on Apache projects and the Jira ITS. Some findings may not transfer to projects that do not use Jira to track issues. Wider studies on link types including additional ITSs would be required to make more general statements about trace link types. We note, however, that even within the Apache ecosystem, trace link usage varies between projects (see Section III-B). Intentionally, the label recovery experiments presented in this work do not presuppose specific link labels so the steps presented here should transfer to other datasets.

VIII. CONCLUSIONS

In this work, we have investigated horizontal traceability from the perspective of issue link labels in open source projects. Our study indicates that, for projects with varying size and complexity, it is possible to achieve fairly high recovery scores (a weighted F1 measure of 0.56–0.70) for trace link label recovery using machine learning techniques, model tuning, and feature selection. Particularly, we show that the set of features, the classifier, and the hyper-parameter settings presented all greatly influence the performance of the label recovery method and careful consideration of validation criteria and available resources should be made before implementing any single solution. While we haven’t observed obvious advantages of pre-training word embeddings in our case study, the positive effect of using metadata of the issue links is decisive. This work also demonstrated the potential of using the machine learning models to predict labels for future links. As the project proceeds, and more training data is available, our method brings improvement on the label prediction performance.

We envision two directions to which this work can directly bring benefits. First, our link label recovery function can be used to support many automated analytic tools. Most of the current automated analytic tools require complete and accurate link labels to aggregate information about certain aspects of the development process. For example, the links related to release planning and stability analysis would be entirely different. The analytic results can be sabotaged if the link labels are incomplete or inaccurate. Our method can be used to support identifying issue links that are relevant to the specific analytic functions. The second direction is to build plugins for ITSs to suggest link labels when the users are creating or inspecting related links using the prediction function. Such suggestions will directly support novice contributors who are not knowledgeable enough about the existing code base or issues to make meaningful and accurate links.

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