LinkFormer: Automatic Contextualised Link Recovery of Software Artifacts in both Project-based and Transfer Learning Settings

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Abstract Software artifacts often interact with each other throughout the software development cycle. Associating related artifacts is a common practice for effective documentation and maintenance of software projects. Conventionally, to register the link between an issue report and its associated commit, developers manually include the issue identifier in the message of the relevant commit. Research has shown that developers tend to forget to connect said artifacts manually, resulting in a loss of links. Hence, several link recovery techniques were proposed to discover and revive such links automatically. However, the literature mainly focuses on improving the prediction accuracy on a randomly-split test set, while neglecting other important aspects of this problem, including the effect of time and generalizability of the predictive models.

In this paper, we propose LinkFormer to address this problem from three aspects: 1) Accuracy: To better utilize contextual information for prediction, we employ the Transformer architecture and fine-tune multiple pre-trained models on textual and metadata of issues and commits. 2) Data leakage: To empirically assess the impact of time through the splitting policy, we train and test our proposed model along with several existing approaches on both randomly- and temporally-split data. 3) Generalizability: To provide a generic model that can perform well across different projects, we further fine-tune LinkFormer in two transfer-learning settings. We empirically show that researchers should preserve the temporal flow of data when training learning-based models to resemble the real-world setting. In addition, LinkFormer significantly outperforms the state-of-the-art by large margins (e.g., 48% improvement of F1-measure in the project-based setting). Furthermore, LinkFormer’s performance in the cross-project setting is on par with its average performance in the project-based case (88% vs. 90% F1-measure). As a result, LinkFormer is capable of extending the knowledge it learned to unseen projects with little to no historical data.

Keywords Link Recovery · Traceability · Software Maintenance · Documentation · Machine Learning · Transformers · Generalizability
1 Introduction

Software traceability aims to facilitate various software management and maintenance tasks such as feature location, defect prediction, impact analysis, software quality measurement, and bug localization [1,2,3,4]. In this work, we focus on recovering links among related code changes and issue reports in a software repository. Conventionally, developers manually include an identifier in a commit to link it to its corresponding issue report(s). However, manually-added links can be often incomplete due to various reasons such as lack of motivation, lack of guidelines, or developers’ negligence, hence the need for automatic solutions. Existing automatic approaches can be divided into two groups of heuristic-based and learning-based methods. Heuristic-based approaches suffer from very low prediction accuracy [5,6,7], hence, learning-based techniques gained popularity. Most recently, Lin et al. [8] employed Transformers to improve traceability through transferring knowledge from a related Software Engineering domain, Code Search. As the technique is examined using only three Python projects, further investigated is required to assess whether its abilities are extendable to a more diverse set of projects.

Existing approaches face several main challenges: low accuracy, potential data leakage, and limited generalization. Currently, compared to the first challenge, the latter two are understudied. A common practice in Machine Learning studies is to randomly shuffle and split data points to train and test models (assuming the data points are independent). They also conjecture future data will be similar to past data which was used to build a learning-based model. However, the temporal flow of data in software repositories is an inherent feature of the collaborative software development process and issues and commits often interact in a causal way with each other. That is, a commit (a bug fix, a feature, etc.) is usually pushed to a repository to address a previously reported issue (a bug report, a feature request, etc.). For instance, user $u$ files an issue $I_1$ to request a new feature. A team member commits a code change $C_1$ to address this issue. After a while, a bug in the committed change is reported through issue $I_2$ which the team fixes through pushing more commits ($C_2, C_3, \text{etc.}$) and so on. Hence, when randomly shuffling data, the above-mentioned temporal flow which can be of importance for link recovery models will be lost. Moreover, random-splitting on a dataset that includes temporal data can cause data leakage and consequently, lead to an overestimation of a model’s accuracy. To the best of our knowledge, the effect of time on the performance of link recovery models is yet to be investigated. The third aspect of link recovery models is how well they can generalize to new projects. Unfortunately, most of the existing approaches are assessed on a limited number of projects (on average 6 projects per study) [8,9,10,11,12]. Moreover, all studies evaluate their proposed approach in a project-based setting. That is, models are trained per project and then evaluated on part of the data of the same project. This setting requires training multiple models, each specific to one project.

To better understand and address these challenges, we propose LinkFormer, a Transformer-based solution that (1) leverages pre-training and fine-tuning of large language models to strengthen accuracy and generalizability, and (2) adopts data and design choices that reflect realistic data properties to avoid data leakage. LinkFormer consists of two main components:

1) Data Component: Our dataset is composed of True and False links among issue and commit pairs. A True Link is a \langle \text{issue,commit} \rangle pair that is manually linked by a contributor, while a False Link is a pair that is not related to each other. These pairs are specifically curated to solve the link recovery task. Compared to existing studies that use a small number of software projects for training and evaluating (on average 6 projects) [8,9,10,11,12], we
extend our previously publicly shared dataset [13] to include the data from two other studies [10,8]. The new dataset includes a combination of features (textual and metadata) from 20 projects containing more than 233 thousand pairs. More specifically, the new dataset is 1.2X bigger than our previously shared dataset [13], 7.3X larger than the dataset by Rath et al. [10], and 46.4X bigger than the dataset by Lin et al. [8]. Aside from the larger side and relevancy of this dataset to the task of link recovery, it also contains a wide variety of projects from different development scopes which are written in various programming languages. To resemble the real-world setting and decrease data leakage impact, we train our model on temporally-split data and show that this choice can significantly affect the performance of the model.

2) Model Component: LinkFormer is based on various Transformer-based architectures fine-tuned using a large and diverse set of software projects’ data. The Transformer architecture is able to extract more contextual information from the data and to decrease the semantic gap between issue reports and commit messages, hence resulting in better accuracy. Semantic gap refers to the problem of semantically-similar \( \langle \text{issue, commit} \rangle \) pairs that are written with different lexicons. Traditional models which rely on extracting exact matches among words, struggle with detecting semantically-similar text with a common context. Pre-trained embeddings can help mitigate this problem. To improve the generalizability of solutions, we transfer the knowledge within the same domain. Then, we use this pre-trained model to predict missing links for four previously unseen projects. Moreover, enhanced parallel computations of Transformer models can result in better runtime characteristics.

We evaluate LinkFormer against three baselines, including both traditional and advanced learning-based models. DeepLink [9] is a deep RNN model exploiting textual data, HybridLinker [13] is an ensemble classical learner, and T-BERT [10] is a Transformer-based model. We asses models in four settings: i) project-based training using randomly-split data, ii) project-based training using temporally-split data, iii) generic model through intermediate fine-tuning, and finally, iv) generic model using a cross-project setup. With the first two, we train and test per project using different splitting choices to investigate the impact of such choice on the performance. With the latter two, we study how generalizable the capabilities of the two pre-trained models across projects are.

Our results indicate that (1) for both project-based and cross-project link prediction, LinkFormer outperforms the state of the art; (2) temporal splitting is needed to avoid data leakage and to ensure a realistic setting, (3) LinkFormer in both intermediate fine-tuning and cross-project settings performs on par with its average performance in the project-based mode. That is, it successfully transfers knowledge from the set of training projects to a set of unseen test projects. Therefore, LinkFormer can be used for prediction in projects that have little or no training data. The main contributions of this work are:

- The LinkFormer dataset: to the best of our knowledge, this is the largest and widest set of software projects used for the link recovery problem (Section 3.1).
- The LinkFormer architecture and model: the proposed approach significantly outperforms the baselines in all project-based and cross-project settings (Section 3.2).
- An empirical assessment of the implications of randomly-split versus temporally-split data points for the link recovery task (Sections 5.1 and 5.2).
- An empirical assessment of the generalizability of LinkFormer (Sections 5.3 and 5.4).
- Openly available source code and dataset.

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\[1\] Our previous dataset (downloaded more than 1900 times) is publicly available on Zenodo: [https://zenodo.org/record/5067833#.Yzv6zuxBuq](https://zenodo.org/record/5067833#.Yzv6zuxBuq)

\[2\] [https://github.com/MalihehIzadi/linkformer](https://github.com/MalihehIzadi/linkformer)
2 Background and Literature

We first provide background information on the problem of link recovery. Then we present an overview of the existing literature addressing this problem and finally the background of our proposed approach.

An issue tracking system contains all the information related to reported bugs, change requests, new features, or tasks for the development of a project. An issue represents the discussion around a topic such as a desired change. It has several information fields including a unique ID, the issue’s type, status, priority, severity, description, creation date, updated date, and resolution information. Issues may optionally contain comments and code snippets to further demonstrate the purpose of an issue. A commit contains all the necessary code changes in the version control system which is utilized for managing and documenting changes during the software development process. It contains fields such as a unique commit ID, commit message, committer ID, author ID, changed files, and their diff which encapsulates the differences between the files of the current and previous states of a repository.

Many aspects of collaborative software development exploit the link between issues and commits. To link an issue and a commit, developers, assigned to solve the issue, add the unique issue ID to its associated commit. Although usually there are guidelines on how to contribute to software projects, there is no guarantee that developers follow them in practice. Reasons such as negligence, deadline pressure, and the cost and effort required to keep well-maintained documentation can result in an incomplete set of links and weak traceability. Guidelines of a software project may vary, however, the general rule for linking is to have at least one issue linked to each commit, to be able to track the reason behind each code change. If an issue requires major changes, it may be connected to multiple commits. Depending on the category and relevance of an issue, it may not need a code change (e.g., when it is a mere question or ask for support), hence, there will not be any links. Moreover, there may exist duplicate or similar issues, that are resolved by the same commit.

Table 1 provides a sample issue and commit from the Apache Beam project. This is an open-source project for defining and executing data processing workflows. The issue summary indicates a bug related to CI/CD tools’ configuration files. The commit is directly related to the above issue. Despite the clear contribution guidelines of this project, the link between this issue and the commit is currently missing from the project. No issue ID or extensive lexical overlap is evident in the provided information which makes it hard for existing solutions to find the connection between them. An automatic approach capable of extracting semantics and contextual information from textual information of such artifacts can facilitate the process of development along with its management and documentation.

2.1 Related Work

Link recovery research can be categorized into two main groups: heuristic-based and learning-based approaches.

Heuristic Approaches: Initially, researchers exploited heuristics to recover links among issues and commits. For instance, ReLink relies on the information provided in developers’

1 https://beam.apache.org/
2 https://github.com/apache/beam/issues/23671
3 https://github.com/apache/beam/commit/df80a0599c4bd6c736bd68874b83cd02c561d1
Table 1: Example of an issue and a commit from the Apache Beam project.

| Issue summary | [Bug]: TPC-DS Jenkins job doesn’t read all data from partitioned files |
|---------------|------------------------------------------------------------------------|
| Issue description | TPC-DS Jenkins job doesn’t read all data from partitioned files from gs://beam-tpcds/datasets/parquet/partitioned path. It can be related to an internal structure of partitioned directories and files that are not properly matched with provided path pattern. |
| Commit message | [TPC-DS] Use “nonpartitioned” input for Jenkins jobs |
| Diff code | in (.test-infra/jenkins/job PostCommit_Java_Tpcds_Dataflow.groovy)  
- `--dataDirectory=gs://beam-tpcds/datasets/parquet/partitioned`  
+ `--dataDirectory=gs://beam-tpcds/datasets/parquet/nonpartitioned`  
in (.test-infra/jenkins/job PostCommit_Java_Tpcds_Spark.groovy)  
- `--dataDirectory=gs://beam-tpcds/datasets/parquet/partitioned`  
+ `--dataDirectory=gs://beam-tpcds/datasets/parquet/nonpartitioned` ... |

changelogs. The authors used keywords such as ‘fixed’ and ‘bug’ or issue ID references in changelogs alongside features extracted from linked issues and commits. MLink [6] is a layer-based approach that exploits both textual and code-related features. PaLiMod [7] uses the analysis of interlinking characteristics of commits and issues. The authors introduced Loners (one commit, one issue) and Phantoms (multiple commits, one issue) as new separated heuristics. Heuristic-based methods suffered from low precision, hence learning-based methods were proposed.

**Traditional Learning Approaches:** RCLinker [14], FRLink [11], and PULink [12] use binary classifiers to address the link recovery problem. RCLinker automatically generates commit messages for commits and feeds them along with issues’ textual information to the classifier. Sun et al. [11] use a set of features including complementary documents such as non-source documents for training FRLink. PULink [12] uses True Links and Unlabeled links to decrease the amount of data needed for training the model. Rath et al. [10] leverage a combination of process and text-related features characterizing issues and code changes to augment a set of existing trace links. This approach achieves very unbalanced precision and recall scores, hence, low F1-measure scores. Hybrid-Linker [13] proposes to use two separate models for learning from textual (issue text, commit message, etc.) and non-textual data (author, committer, timestamps, etc.). Although learning-based models are more capable compared to heuristic-based ones, there is still room for improving the accuracy of results, particularly when training data is insufficient. Furthermore, training and assessing only based on a set of limited projects, platforms, and programming languages threatens the generalizability of the findings of these studies.

**Deep Learning Approaches:** In 2019, Xie et al. [15] employed a deep learning technique (DeepLink [16]) originally used for identity linkage. The authors exploited class embedding in commit codes to create a knowledge graph. They used CBOW and Word2Vec embeddings for commit and issue documentation. Unfortunately, their knowledge graph and replication package are not accessible. Ruan et al. [9] proposed a semantically-enhanced link recovery method based on DeepLink [16]. They used the textual data of issues and commits and omitted their comments to avoid introducing noise. This method requires a large amount of
data and high computational resources. Most recently, Lin et al. [8] employed Transformers to improve traceability for software artifacts. The authors used a pre-trained language model related to the CodeSearch task, and then, experimented with three settings of Single, Twin, and Siamese networks for fine-tuning this model. Their results indicate that the Single-BERT architecture obtains the most accurate results, while the Siamese-BERT network reduces execution time. Although using pre-trained models the authors were able to improve the accuracy of suggested links, model was trained and tested on a limited number of projects (Pgcli, Flask, and Keras) all written in Python.

2.2 Transformers

Recently, there have been significant improvements with the introduction of the self-attention mechanism in the Transformer architecture which is a sequence-to-sequence model for transforming a given sequence of elements into another form [17]. Attention enables Transformer models to focus on selective parts of inputs, thus generating more relevant outputs [18]. Transformers outperform deep learning models such as RNNs and Long Short Term Memory Networks (LSTM) on multiple Natural Language Processing (NLP) tasks [17]. They are more parallelizable and require significantly less time to train compared to RNNs. A vanilla Transformer architecture consists of two main components, an encoder, and a decoder. Initially, the Bidirectional Encoder Representations from Transformers (BERT) [19] were proposed to pre-train deep bidirectional representations employing two pre-training tasks, namely, Masked Language Modeling (MLM) and Next Sentence Prediction (NSP). DistilBERT [20] is a smaller general-purpose language model which combines language modeling and distillation. Compared to BERT, DistilBERT is 40% smaller in size, and 60% faster. RoBERTa (Robustly-optimized BERT approach) [21] modifies BERT’s MLM task by using a dynamic masking technique, and eliminates its NSP task. Finally, ALBERT [22] focuses on lowering the memory consumption while increasing training speed. ALBERT achieves 80% reduction in the parameters of the projection block, and a small decrease in performance compared to BERT. In this work, we employ the above-mentioned three recent and high-performing Transformer models; DistilBERT, RoBERTa, and ALBERT as part of our proposed approach.

3 The LinkFormer Approach

Figure 1 depicts the general workflow of LinkFormer. Our approach consists of two main phases; (i) data processing, and (ii) model training. We first collect and process the largest set of software projects (to the extent of our knowledge) used for investigating the \langle\text{issue, commit}\rangle pairing problem. We then pre-train our Transformer model in different settings: project-based, fine-tuned, and cross-project settings. We also employ two different splitting policies: random and temporal. In this section, we elaborate more on the approach.

3.1 Dataset

Different studies addressing the link recovery problem have relied on different sets of software projects. To close the gap by providing a more diverse and inclusive set of projects, we decided to select all projects from the three recent studies in the field [10][13][8].
Table 2: General information of the software projects in our dataset. (part 1) (ITS stands for Issue Tracking System and VCS stands for version control system)

| Source      | Project | #Stars | #Forks | #Contribs | #True Links | ITS/VCS     |
|-------------|---------|--------|--------|-----------|-------------|-------------|
| Rath et al. | Maven   | 3,100  | 2,200  | 153       | 1,676       | Jira/GitHub |
|             | Pig     | 648    | 460    | 11        | 1,966       | Jira/GitHub |
|             | Derby   | 273    | 132    | 4         | 3,815       | Jira/GitHub |
|             | Drools  | 4,300  | 2,200  | 79        | 3,846       | Jira/GitHub |
|             | Infinispan | 950    | 566    | 166       | 4,640       | Jira/GitHub |
| Mazraei et al. | Cassandra | 7,200  | 3,100  | 361       | 147         | Jira/GitHub |
|             | Freemarker | 733    | 219    | 30        | 178         | Jira/GitHub |
|             | Netbeans | 1,800  | 687    | 175       | 1,370       | Jira/GitHub |
|             | Calcite | 3,000  | 1,700  | 294       | 3,059       | Jira/GitHub |
|             | Arrow   | 9,400  | 2,300  | 719       | 5,252       | Jira/GitHub |
|             | Airflow | 25,500 | 10,400 | 2,035     | 5,295       | Jira/GitHub |
|             | Beam    | 5,400  | 3,500  | 903       | 5,750       | Jira/GitHub |
|             | Iss     | 684    | 281    | 47        | 8,486       | Jira/GitHub |
|             | Groovy  | 4,500  | 1,700  | 330       | 8,851       | Jira/GitHub |
|             | Ignite  | 4,100  | 1,800  | 277       | 9,998       | Jira/GitHub |
|             | Flink   | 18,600 | 10,600 | 1,043     | 14,472      | Jira/GitHub |
|             | Ambari  | 1,600  | 1,400  | 134       | 35,590      | Jira/GitHub |
| Lin et al.  | Pgcli   | 10,300 | 466    | 136       | 643         | GitHub/GitHub |
|             | Keras   | 55,000 | 19,100 | 1,014     | 719         | GitHub/GitHub |
|             | Flask   | 58,600 | 15,500 | 653       | 1,158       | GitHub/GitHub |

Rath et al. [10] shared six projects (all in Java) and Lin et al. [8] experimented on three projects (all in Python). In our previous study [13], we provided 12 projects (with 8 different programming languages of Python, Java, C++, C#, Groovy, Kotlin, JavaScript, Scala). Groovy is the only common project [10,13]. Table 2 and Table 3 provide a summary of the projects’ information included in our study. These projects have a diverse range of stars, forks and number of True Links. Each focuses on a different domain of Software Engineering. Commits in all projects are collected from GitHub, however, issues are retrieved from either Jira or GitHub. The dataset covers different programming languages including Python,
| Source         | Project                  | Scope/Domain                  | Top 3 Languages | Last Activity |
|---------------|--------------------------|-------------------------------|-----------------|---------------|
| Rath et al.   | Maven                    | software project management  | Java            | Apr 2022      |
|               | Pig                      | dataflow programming env.     | Java            | Jan 2022      |
|               | Derby                    | relational database engine    | Java            | Aug 2019      |
|               | Drools                   | rule engine for Java          | Java            | Apr 2022      |
|               | Infinispan               | NoSQL cloud data store        | Java            | Apr 2022      |
| Mazrae et al. | Cassandra                | NoSQL database                | Java            | Apr 2022      |
|               | Freemarker               | template engine               | Java            | Jun 2022      |
|               | Netbeans                 | IDE                           | Java            | Apr 2022      |
|               | Calcite                  | data management               | Java            | Apr 2022      |
|               | Arrow                   | data analytics app developing | C++, Java, Go   | Apr 2022      |
|               | Airflow                  | monitoring workflow platform  | Python           | Apr 2022     |
|               | Beam                    | data processing framework     | Java, Python    | Apr 2022      |
|               | Isis                     | domain-driven web framework   | Java, Kotlin, JS | Apr 2022 |
|               | Groovy                   | programming language for JVM  | Java, Groovy    | Apr 2022      |
|               | Ignite                   | distributed database          | Java, C#, C++   | Apr 2022      |
|               | Flink                    | data processing framework     | Java, Scala, Python | Apr 2022 |
|               | Ambari                   | Hadoop management tool        | Java, JS, Python | Sep 2022 |
| Lin et al.    | Pgcli                    | database CLI                  | Python           | Apr 2022      |
|               | Keras                    | deep learning library         | Python           | Apr 2022      |
|               | Flask                    | micro-web framework           | Python           | Apr 2022      |

Java, C++, C#, Groovy, Kotlin, Java Script, and Scala. And finally, as it can be seen from the Table 3 all projects of this dataset are actively maintained except Derby which is last updated in August 2019. Project scope diversity gives us an opportunity to study the behavior of our model in different domains, and also adds to the generalizability of the approach. For all the 20 remaining projects, we collect any missing information associated with their issues and commits from GitHub or Jira to complement the dataset. For instance, as Lin et al. [8] only use textual information of issues and commits, it does not include non-textual features such as metadata of authorship or timestamps of artifacts. In such cases, specific crawlers were written to gather information from the GitHub repositories using GraphQL API.

Features The collected dataset contains both textual and metadata of issues and commits. The textual data consists of (i) natural language text, i.e., issue title, issue description, and commit message, and (ii) source code from code diff of a given commit. We first tokenize and remove stop words from textual information. The metadata of issues and commits include author, committer, timestamps, and categorical data consisting of issue type and commit status. Every project in a hosting platform can define a different set of values for the issue type. To uniform the different values we keep the three main categories of issue types, namely, task, feature, and bug. Similarly, for commit status types, we select the main categories of closed and resolved. Next, we encode these categorical features using the one-hot encoding method. Git commits store two timestamps, the author date and the committer date. The former is when the commit was originally made, while the latter, denotes the last date the commit was modified. Usually these two are identical, however, certain commands such as rebasing, change a commit, hence, changing the committer date. As Flint et al. [23] recommend to use the author date instead of committer date, and these two are correlated features, we only use author date for training the models. The final list
of features includes creator, author, committer, closed, resolved, bug, feature, task, committed_time, authored_time, created_date, and updated_date.

Negative Sampling  To conduct supervised learning, one needs both True Link and False Link labels. We obtain True Links from repositories. True Links are \langle issue, commit \rangle pairs which are directly connected by developers through recording the issue ID in the relevant commit title or body. To create False Links, we use an standard negative sampling technique proposed in the literature \cite{13,11,9}. Negative sampling refers to the process of creating False Links among \langle issue, commit \rangle pairs. This technique connects the previously paired issues from the True Link set to all unrelated commits (not currently in the True Link set). The downside of this method is the large number of created False Links since for each of commits \( c \) in the True Link set total of \( i - c \) (\( i \) being the total number of issues for that project) False Link will be created. To solve this problem, we adopt a filtering criterion to reduce the number of False Links. A commit’s submission date is compared against an issue’s submission date. If this difference is less than seven days, the pair is included in the False Link set, otherwise, it is disregarded \cite{13,11,9}. Lastly, to provide a balanced dataset for training purposes, we randomly select an equal number of False Links as True Links for each project.

3.2 Model

For the past few years, Transformer models have significantly impacted the NLP domain. Now, Pre-trained models such as BERT can be fine-tuned using additional output layers to create state-of-the-art models without major task-specific architecture modifications. Recently, these NLP-based models are also being employed for various Software Engineering and source code-related tasks \cite{24,25,26}. In this work, we leverage the power of pre-trained models and fine-tune it on our dataset. Figure 2 depicts the main architecture of LinkFormer.

3.2.1 Pre-trained Model

Given that pre-training from scratch is highly expensive, we employ the existing pre-trained models in the NLP domain, and build upon their knowledge to solve our downstream Software Engineering task: the link recovery problem. To do so, we exploit three well-assessed and successful variants of the BERT architecture, RoBERTa \cite{21}, DistilBERT \cite{20}, and ALBERT \cite{22} introduced in the Background section on Transformers (Section 2.2). We have selected these variants with three aspects in mind: high accuracy, reasonable model size, and short inference time. The pre-trained language models have an extensive natural language comprehension ability. By leveraging such models, LinkFormer is able to better understand and utilize the semantics and context of a \langle issue, commit \rangle pair.

The input sequence to our model consists of the pre-processed \langle issue, commit \rangle pairs and their corresponding labels (True Link and False Link) indicating whether each pair is related or not. For each issue, we concatenate the issue’s summary with its metadata to generate the issue vector. Similarly, for a given commit, we combine the message with its metadata to build the commit vector. It is worth mentioning that our approach is independent of the programming language of software projects. As we do not apply excessive text preprocessing or source code processing, LinkFormer can easily be used for any new project.
3.2.2 Fine-tuning

Next, fine-tuning these pre-trained models using our dataset containing more than 233K \((\text{issue, commit})\) pairs, adjusts LinkFormer’s parameters to the link recovery problem. We add a fully-connected classification layer on top to fine-tune the underlying pre-trained model (RoBERTa, DistilBERT, or AlBERT). LinkFormer uses the softmax activation function in the output layer to generate probability distributions.

4 Experiment Design

In this section, we first present our research questions. Next, we introduce the evaluation metrics used for comparing the performance of our model against baselines. Then, we review the selected baselines to evaluate our proposed model against. Lastly, we review the configuration and implementation details we used to develop our approach.

4.1 Research Questions

We define four Research Questions (RQ) to measure the effectiveness of our proposed approach in both project-based and cross-project settings.
RQ1: How accurately does LinkFormer recover links in a project-based setting on randomly-split data? We first train and evaluate the models on each project separately. This is the basic setting mostly used in the literature. The samples in the dataset are shuffled randomly, and then 80% of data is used for training and the rest for testing.

RQ2: How accurately does LinkFormer recover links in a project-based setting on temporally-split data? To assess whether random splits might lead to accidental data leaks due to time dependencies, we also train the models where all samples are temporally sorted. The first 80% of each project’s data is used for training and the rest for testing.

RQ3: How accurately does LinkFormer perform when employing intermediate fine-tuning? In this study, we train a generic model capable of recovering links for projects with insufficient data. We first pre-train LinkFormer on 80% of the project’s data (16 projects). We then update the model’s parameters through an extra step of intermediate fine-tuning and validating it using 80% and 10% of the data of each of the four test projects. Through this intermediate training phase, not only the model embeds a body of knowledge from the initial 16 projects (transfer learning through the use of pre-trained models), it also learns from a portion of historical data from four test projects. Finally, we evaluate the model on the remaining 10% of the data from each project.

RQ4: How accurately does LinkFormer perform in a cross-project setting? In the second mode of transfer learning, we assess the model’s performance on projects for which it has not seen any historical information. That is, the pre-trained model (trained on the data of 16 projects) is directly used for evaluation on the test set of the four unseen test projects. We use a cross-fold validation setting here. That is, we divide the dataset into five folds; each fold containing four projects. In each experiment, we use four folds for pre-training and one fold for testing. We rotate these folds until all 20 projects are assessed in the testing set. Experiments for RQ3 and RQ4 are based on temporally-split data.

4.2 Evaluation Metrics
We use the F1-measure as the standard metric for the link recovery task to assess the models’ performance. A link recovery model with low precision predicts many links that are not there. Thus, the suggested links need to be manually re-checked, e.g., by a human expert. Moreover, a link recovery method with low recall fails to retrieve the actual linked ⟨issue, commit⟩ pairs in the data. Thus, a good predictive model should have both high precision and recall. Hence, we compare the performance of models mainly based on their F1-measure, defined as the harmonic mean of precision and recall:

\[
F1 = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}
\]  

4.3 Baseline Approaches
To carry out a comprehensive evaluation, we take three recent approaches for link recovery as our baselines [9][13][8]. Hybrid-Linker [13] is based on a traditional supervised classifier, namely decision trees. Ruan et al. [9] employ an RNN, and T-BERT [8] uses a state-of-the-art Transformer model for NLP. Hybrid-Linker [13] extracts different features from data and separates them into a textual and non-textual channels. Textual data of projects is fed to a Gradient Boosting model, while non-textual data is used to train an ensemble model based on Gradient Boosting and XGBoost techniques. Hybrid-Linker combines the decisions of
these separate models to obtain the final result. Ruan et al. [9] uses a word embedding module, an RNN module, and a similarity module as part of their link recovery method. Lin et al. [8] generates trace links between source code and natural language artifacts using various Transformer-based architectures namely Single-BERT, Twin-BERT, and Siamese-BERT. According to the authors, the Single-BERT architecture generates the most accurate links. Hence, we use their best-performing model, Single-BERT, in our experiments [8]. It is important to note that all the baseline approaches shuffle their data randomly, and then split their training and test set and train their models. Therefore, they do not report the performance of their model on temporally-sorted data. Moreover, HybridLinker and DeepLink are both only designed for training and testing in a project-based setting. Finally, none of the baselines evaluate the performance of their proposed model on unseen projects. Hence, we include DeepLink, HybridLinker, and T-BERT as baselines for RQ1 and RQ2. However, for RQ3 and RQ4 (transfer learning mode), we only take T-BERT as the baseline as it is the only approach based on pre-trained models. Note that, although T-BERT is also pre-trained on other sources of data (CodeSearchNet dataset), to avoid putting T-BERT at a disadvantage in RQ3, we fine-tune this baseline on 80% of data of each four test projects. This is similar to how we treat our proposed approach, except that our models are not pre-trained on the CodeSearchNet dataset.

4.4 Implementation and Configuration

For pre-processing, we use the Pandas Python library [27]. To train traditional classifiers, we use the Sci-Kit Learn library. Furthermore, we use the HuggingFace [7] and Simple-Transformers [8] libraries for the implementation of LinkFormer. We set the learning rate to $3 \times 10^{-5}$, the number of fine-tuning epochs to 6, the maximum input length to 512, and the batch size to 32. For all baselines, we relied on their provided replication package. In the project-based setting, we split each project’s data with 80/10/10 percent ratio per training, validation, and testing sets, respectively. In the fine-tuning setting, we split the projects into five folds. Each time, we use four folds (16 projects) for fine-tuning, and one fold for testing (4 projects). All our experiments have been conducted on a server equipped with one GeForce RTX 2080 GPU, an AMD Ryzen Threadripper 1920X CPU with 12 core processors, and 64G of RAM. We release our source code and dataset online [9].

5 Results

In this section, we provide the results of our experiments. We compare our proposed model against three baselines including a traditional learning-based model [13], a deep learning model (RNN) [9], and a Transformer-based model [8]. We report the results based on two data splitting choices; random and temporal. We also train and evaluate the models in the project-based and transfer learning modes.

https://scikit-learn.org
https://huggingface.co
https://github.com/ThilinaRajapakse/simpletransformers
https://github.com/MalihehIzadi/linkformer
Table 4: Project-based training and assessment (RQ1: random data split)

| Project    | Deeplink | Hybrid-Linker | T-BERT | LinkFormer (Proposed) |
|------------|----------|---------------|--------|------------------------|
| Maven      | 0.66     | 0.81          | 0.90   | 1.00                   |
| Pig        | 0.66     | 0.74          | 1.00   | 1.00                   |
| Derby      | 0.63     | 0.85          | 1.00   | 1.00                   |
| Drools     | 0.64     | 0.84          | 1.00   | 1.00                   |
| Infinispan | 0.55     | 0.87          | 1.00   | 1.00                   |
| Maven      | 0.80     | 0.91          | NA     | 0.90                   |
| Freemarker | 0.89     | 0.87          | 0.11   | 0.97                   |
| Netbeans   | 0.59     | 0.88          | 0.65   | 0.94                   |
| Calcite    | 0.66     | 0.87          | 0.94   | 0.99                   |
| Arrow      | 0.43     | 0.84          | 0.94   | 0.97                   |
| Airflow    | 0.45     | 0.86          | 0.97   | 0.98                   |
| Beam       | 0.66     | 0.86          | 0.70   | 0.95                   |
| Isis       | 0.79     | 0.88          | 0.92   | 0.92                   |
| Groovy     | 0.64     | 0.88          | 0.97   | 0.96                   |
| Ignite     | 0.64     | 0.90          | 0.81   | 0.94                   |
| Flink      | 0.72     | 0.91          | 0.94   | 0.97                   |
| Ambari     | 0.82     | 0.96          | 1.00   | 0.99                   |
| Pgcli      | 0.49     | 0.67          | 0.89   | 0.95                   |
| Keras      | 0.35     | 0.75          | 0.97   | 0.99                   |
| Flask      | 0.42     | 0.68          | 0.74   | 0.91                   |
| Average score | 0.62  | 0.84          | 0.86   | 0.97                   |
| Standard deviation | 0.15 | 0.07          | 0.21   | 0.03                   |

5.1 RQ1: Project-based Training with Random Data Split

Table 4 provides the results of the first experiment. In this setup, we train each model per project (project-based mode). Data of each project is split randomly into train and test sets. The last two rows present the mean average score of a model and its standard deviation over all projects. All the results obtained in the randomly-split case are consistent with previous studies. However, note that for the Cassandra project T-BERT’s replication package encounters errors and does not provide predictions. Hence, the results for this project/model are Not Available (NA). This may be due to the fact this project has the lowest number of True Links in the dataset. In this setting, LinkFormer outperforms DeepLink, HybridLinker, and T-BERT by 56%, 15%, and 13%, respectively. Although RoBERTa-based LinkFormer obtains the best results, its difference with the other two architectures (DistilBERT and ALBERT) is not significant.

5.2 RQ2: Project-based Training with Temporal Data Split

Table 5 presents the results of the second experiment. Contrary to the previous setup, we split the data of each project temporally. We use the first 80% and 10% for training and validation, and the last 10% of data (newest data) for testing the models. The results show that LinkFormer’s performance surpasses all baselines based on the F1-measure of predictions for this setting as well. More specifically, LinkFormer outperforms DeepLink, HybridLinker, and T-BERT by 67%, 34%, and 48%, respectively. Similar to RQ1 results, RoBERTa-based LinkFormer obtains the best results in this case as well, however, it is closely followed by
Table 5: Project-based training and assessment (RQ2: temporal data split)

| Project  | Deeplink | Hybrid-Linker | T-BERT | LinkFormer (Proposed) |
|----------|----------|---------------|--------|------------------------|
| Maven    | 0.79     | 0.85          | 0.78   | 0.97                   | 0.94       | 1.00         |
| Pig      | 0.83     | 0.76          | 0.75   | 0.99                   | 0.99       | 1.00         |
| Derby    | 0.47     | 0.86          | 0.54   | 1.00                   | 0.99       | 1.00         |
| Drools   | 0.47     | 0.74          | 0.94   | 0.99                   | 0.99       | 1.00         |
| Infinispan| 0.57     | 0.85          | 0.43   | 0.99                   | 0.99       | 0.99         |
| Maven    | 0.75     | 0.63          | NA     | 0.77                   | 0.86       | 0.35         |
| Freemarker | 0.13   | 0.42          | 0.16   | 0.71                   | 0.57       | 0.64         |
| Netbeans | 0.09     | 0.44          | 0.81   | 0.90                   | 0.90       | 0.90         |
| Calcite  | 0.44     | 0.60          | 0.91   | 0.97                   | 0.97       | 0.98         |
| Arrow    | 0.43     | 0.69          | 0.91   | 0.97                   | 0.97       | 0.97         |
| Airflow  | 0.64     | 0.54          | 0.60   | 0.98                   | 0.98       | 0.97         |
| Beam     | 0.54     | 0.58          | 0.50   | 0.75                   | 0.69       | 0.88         |
| Isis     | 0.54     | 0.40          | 0.12   | 0.70                   | 0.60       | 0.69         |
| Groovy   | 0.60     | 0.54          | 0.50   | 0.91                   | 0.88       | 0.87         |
| Ignite   | 0.52     | 0.78          | 0.52   | 0.94                   | 0.92       | 0.92         |
| Flink    | 0.65     | 0.68          | 0.73   | 0.94                   | 0.92       | 0.92         |
| Ambari   | 0.67     | 0.84          | 0.37   | 0.94                   | 0.95       | 0.93         |
| Pgcli    | 0.62     | 0.72          | 0.70   | 0.75                   | 0.80       | 0.82         |
| Keras    | 0.50     | 0.78          | 0.82   | 0.90                   | 0.89       | 0.89         |
| Flask    | 0.57     | 0.62          | 0.50   | 0.93                   | 0.93       | 0.91         |

| Metric    | Average score | Standard deviation |
|-----------|---------------|---------------------|
|           | 0.18          | 0.14                |

our other two models (DistilBERT and AlBERT). In the following, we compare the models’ performance based on different factors.

Projects: Inspecting the results per project indicates that a project’s characteristics impact the performance of a given model. These characteristics potentially include its programming language, scope, and data quality/quantity of a project. In both data splitting settings, LinkFormer obtains the lowest standard deviation compared to all the baselines. That is, Linkformer performs comparably on all projects, thus providing more stable results. For instance, in the temporal splitting mode, LinkFormer scores 90% F1-measure on average with a standard deviation of 10%. However, T-BERT has the highest standard deviation in both splitting cases, performing on a wide range of scales per project (on average 61% F1-measure with a standard deviation of 23%). Another factor that can be considered is the difference among data sources. For instance, the five projects from Rath et al.’s study [10] (the first five projects in Table 5) occasionally contain tags. The existence of these tags can affect the performance of a learning-based model on these projects, i.e., it can be generally higher than other projects.

Splitting policy: Comparing the results from the first two RQs, it is evident that all approaches (baselines as well as the proposed approach) take advantage of temporal data leakage in the randomly split data. Thus, for a realistic assessment of the performance in practice (in which there can be no leakage from future, not yet available data), training, validation, and test data must follow a temporal split, as we adopted in RQ2.
Table 6: Transfer learning (RQ3: fine-tuning)

| Project | T-BERT | LinkFormer (Proposed) | RoBERTa | DistilBERT | ALBERT |
|---------|--------|------------------------|---------|------------|--------|
| Maven   | 0.84   | 0.99 | 1.00 | 0.99       |
| Netbeans| 0.90   | 0.92 | 0.93 | 0.90       |
| Flask   | 0.94   | 0.90 | 0.92 | 0.87       |
| Beam    | 0.67   | 0.75 | 0.67 | 0.70       |
| Calcite | 0.84   | 0.97 | 0.96 | 0.96       |
| Ambari  | 0.78   | 0.95 | 0.95 | 0.95       |
| Cassandra| NA    | 0.88 | 0.80 | 0.85       |
| Freemaker | 0.55 | 0.74 | 0.78 | 0.74       |
| Derby   | 0.84   | 0.99 | 0.97 | 0.72       |
| Drools  | 0.80   | 0.99 | 0.99 | 0.85       |
|Pg      | 0.79   | 0.99 | 0.95 | 0.77       |
| Flink   | 0.55   | 0.93 | 0.90 | 0.87       |
| Infinispan | 0.81 | 0.99 | 0.99 | 0.97       |
| Arrow   | 0.91   | 0.97 | 0.94 | 0.94       |
| Airflow | 0.78   | 0.95 | 0.93 | 0.93       |
| Isis    | 0.23   | 0.70 | 0.72 | 0.63       |
| Ignite  | 0.82   | 0.92 | 0.90 | 0.92       |
| Groovy  | 0.39   | 0.88 | 0.83 | 0.87       |
| Keras   | 0.79   | 0.83 | 0.75 | 0.69       |
| Pgcli   | 0.53   | 0.82 | 0.76 | 0.74       |
| Average score | 0.72 | 0.90 | 0.88 | 0.84       |
| Standard deviation | 0.18 | 0.09 | 0.10 | 0.10       |

5.3 RQ3: Generic Models via Intermediate Fine-tuning

Next, we present the results of our experiments on the two pre-trained models (T-BERT and LinkFormer) to assess the impact of transfer learning in fine-tuning mode. Table 6 provides the results of this experiment. Each fold contains 16 projects for training and four projects for testing. We report the evaluation results for these four projects in each fold. Folds are separated with horizontal lines. As mentioned earlier, we only include the baseline based on the pre-training technique (T-BERT [8]). We exclude the other two baselines (HybridLinker [13] and DeepLink [9]) as they are originally proposed and designed for project-based training and testing, hence they perform very poorly on unseen projects without utilizing the transfer learning technique. Note that in this experiment, we also fine-tune T-BERT on the 80% data of the four test projects (just as we do for our proposed approach). Regarding the average F1-measure over all folds, LinkFormer outperforms T-BERT by 25% in this mode. Moreover, inspecting the results per project, for 19 out of 20 projects, LinkFormer outperforms T-BERT by large margins. Only, for the Flask project, both approaches perform on par (92% and 94% F1-measure). Similar to previous RQs’ results, RoBERTa-based LinkFormer obtains the best results. Finally, LinkFormer exhibits a lower standard deviation than T-BERT, indicating a more stable performance across the five folds and all projects.
Table 7: Transfer learning (RQ4: cross-project mode)

| Project   | T-BERT | LinkFormer (Proposed) | RoBERTa | DistilBERT | AlBERT |
|-----------|--------|------------------------|---------|------------|--------|
| Maven     | 0.89   | 0.99                   | 0.99    | 0.96       |        |
| Netbeans  | 0.85   | 0.91                   | 0.88    | 0.89       |        |
| Flask     | 0.50   | 0.84                   | 0.88    | 0.76       |        |
| Beam      | 0.45   | 0.70                   | 0.65    | 0.65       |        |
| Calcite   | 0.83   | 0.97                   | 0.97    | 0.97       |        |
| Ambari    | 0.35   | 0.95                   | 0.96    | 0.96       |        |
| Cassandra | NA     | 0.88                   | 0.83    | 0.80       |        |
| Freemarket| 0.54   | 0.85                   | 0.80    | 0.74       |        |
| Pig       | 0.71   | 0.98                   | 0.96    | 0.94       |        |
| Derby     | 0.53   | 0.98                   | 0.97    | 0.89       |        |
| Drools    | 0.89   | 0.98                   | 0.97    | 0.97       |        |
| Flink     | 0.70   | 0.92                   | 0.91    | 0.90       |        |
| Infinispan| 0.42   | 0.98                   | 0.98    | 0.98       |        |
| Arrow     | 0.86   | 0.97                   | 0.96    | 0.97       |        |
| Airflow   | 0.60   | 0.97                   | 0.95    | 0.96       |        |
| Jira      | 0.11   | 0.52                   | 0.65    | 0.63       |        |
| Ignite    | 0.58   | 0.91                   | 0.91    | 0.93       |        |
| Groovy    | 0.47   | 0.86                   | 0.85    | 0.83       |        |
| Pgcli     | 0.59   | 0.70                   | 0.77    | 0.75       |        |
| Keras     | 0.80   | 0.69                   | 0.76    | 0.75       |        |
| Average score | 0.61 | 0.88                   | 0.88    | 0.86       |        |
| Standard deviation | 0.21 | 0.12                   | 0.10    | 0.11       |        |

5.4 RQ4: Generic Models via Cross-project Training

Table 7 presents the results of the final experiment. Considering the average F1-measure over all folds, LinkFormer outperforms the baseline by 49% in the cross-project mode. Compared to the results of RQ3, the average performance of both models decreases as we move from the fine-tuned mode to the cross-project setting. This is probably due to the fact that the model does not consume any information from a project in the cross-project setting. Similar to previous experiments, LinkFormer exhibits a lower standard deviation than the baseline model, T-BERT. Thus, LinkFormer displays a more stable performance across the five folds and all projects. Finally, RoBERTa-based LinkFormer obtains the best results, closely followed by DistilBERT- and AlBERT-based LinkFormer.

6 Discussion

To address the link recovery problem, we incorporate a combination of textual (text of issues, commit message) and metadata (author, committer, timestamps, type, status, etc.) of issue reports and commits to train our model. To better exploit the contextual information in issues and commits, and to be able to transfer knowledge for use on projects with insufficient data, we employ pre-trained Transformer models. Based on the results of our empirical assessment, we first discuss the findings and their implications. We then briefly discuss the runtime
characteristics of LinkFormer as a noteworthy feature. Finally, we present a few potential directions for future work.

6.1 Splitting Data Policy and Data Leakage

The notion of time impacts the link recovery problem due to several reasons including (1) the interactive nature of the life-cycle of open-source software development and (2) the change in the flow of a project and its evolution. Our findings also indicate that time is indeed an important factor worthy of consideration when studying the \textit{(issue, commit)} link recovery problem. The results of RQ1 and RQ2 reflect the impact of the choice of data splitting policies for training and testing sets (random and temporal) on the performance of a model. Although the behavior varies per project as well as per model, all approaches are on average negatively affected when moving from random to temporal policy. That is, previous studies are prone to overestimation in the case of randomly-split data (on average for all considered projects). Some approaches are drastically affected (e.g., T-BERT model with 25% drop in the average F1-measure), while others are more robust when (i.e., LinkFormer is the least affected model with only 7% reduction in the average F1-measure) facing this change. The extent and the reasons for such impact should be further investigated. Data leakage is the key reason for higher performance on randomly-split data. That is, when shuffling datasets randomly, one may accidentally feed future data into the learning-based model.

The common assumption that each data point is an independent random variable can cause problems when training models for link recovery. Issues and commits usually connect to each other in a temporal and causal sense. For example, an open-source project is normally started through a number of initial code commits, after which a series of issue reports can be filed containing identified bugs in the committed code, feature requests, assigned tasks to members and more. As a result, new commits are pushed to the project and the cycle continues. Hence, issues and commits are intertwined and both affect the project evolution over time. However, despite the temporal and causal nature of this problem, former studies simply shuffle the data randomly to create, train and evaluate data.

To the best of our knowledge, Rath et al. [10] is the only study to hint at the notion of time in this domain. The authors take time as an extra feature when training the models. However, they do not analyze the impact of different data splitting techniques, nor do they assess all types of issues (only bug- and implementation-related issues are considered). Moreover, they use a classical J48 algorithm to train multiple project-based classifiers. In this study, we experiment with different splitting settings and empirically show their impact. We also train more accurate and generic models using deep pre-trained models to improve upon generalizability. Hence, we only need a single model to recover links for different types of issues, and for different projects.

\textbf{Recommendation:} Taking the time-sensitivity of this problem into consideration, to simulate the performance of a learning-based model in a real-world setting, this study recommends the use of the temporal splitting policy to avoid feeding any future data into learning-based models.

6.2 Generalizability

We believe a generic model should be able to predict missing links even for new projects with insufficient data. To do so, we trained our generic LinkFormer model in both fine-tun-
ing and cross-project settings to transfer knowledge to unseen software projects. Considering the results from our four experiments in different settings, LinkFormer's performance in the transfer learning modes (fine-tuning and cross-project), is on par with the project-based mode (temporal split). Moreover, the low standard deviation of LinkFormer indicates more stable performance across all projects in all settings. Therefore, we believe our proposed approach benefits from higher generalizability and can be used for predicting links for any unseen project with little to no data. T-BERT, as a model pre-trained initially on the CodeSearchNet dataset and then enhanced through fine-tuning on our dataset, also performs similarly in the transfer and project-based modes. However, its accuracy in both cases (fine-tuned and cross-project) remains much lower compared to LinkFormer.

Recommendation: Considering the power of pre-trained models and the characteristics of the link recovery problem, we recommend that researchers invest in building more generalizable models that are applicable for various types of projects with stable performance.

6.3 Runtime Characteristics

In practice, one needs efficient models in addition to accurate prediction. Fortunately, LinkFormer provides good runtime characteristics. It is only logical that training each project individually takes less time than training a generic model using batches of projects altogether. For instance, in the project-based mode, training LinkFormer (DistilBERT version) only takes 8 minutes on average per project. However, the generic model in the cross-project setting with the same architecture takes 43 minutes to fully train. This is expected as the generic model is trained on more data. Note that the training time is a one-time cost. LinkFormer’s inference time is quite low. For instance, it takes 12 seconds to complete the predictions for the whole test set of the Flink project.

Recommendation: When choosing the best architecture for a given project, one can consider various practical factors including high accuracy along low training and inference time.

6.4 Future Direction

In this work, we focused on improving the accuracy of link recovery techniques for one-to-one links among issues and commits for collaborative software development. Moreover, we considered different angles of this problem including temporal aspects of data and generalizability of the models. Future approaches can extend this work to include many-to-many links as well. Another potential direction for future work is to devise more suitable methods to process source code and extract the relevant information for more accurate linking in the cross-project setting (without introducing large computational overhead to the model). Moreover, we currently build and use balanced datasets to train our models. It is also possible to apply balancing techniques in the learning model itself. The impact of different balancing techniques can then be further inspected. Another possible future direction is to apply LinkFormer to other software artifacts, namely, test cases, requirements documentation, etc. Finally, the negative sampling technique can also be further enhanced. Grammel et al. [28] investigated community involvement in the closed-source IBM Jazz projects. They found that the lifetime of community-created issues is handled differently than those created by project members. More specifically, it can take longer to address the former. Although
we consider the role of issue openers in our models, we have a fixed-length window for negative sampling. Future research can propose new negative sampling techniques that can take this into account, hence improving upon the performance of predictive models.

6.5 Threats to Validity

In the following, we discuss the threats to the validity of this work, organized as internal, external, and construct threats.

Internal Validity: Internal validity is the extent to which a piece of evidence supports a claim about cause and effect, within the context of a particular study [29]. The first threat to internal validity is the reliability of True Links and False Links used in our study. To mitigate this threat, we used or complemented the existing datasets commonly exploited in the literature [13,10,8]. Reusing the data which have been used in similar studies increases the reliability of the data. Because of the large number of possible False Links, we relied on the heuristics proposed by previous work [13,11]. Finally, while creating a balanced dataset for projects, we randomly selected from the set of False Links to avoid introducing selection bias. Although each of these datasets is validated by other researchers [10,8,13], incorrect links may still be present due to human error. Time also plays a role when generating the False Links using a negative sampling technique. Each project has several date fields which are used for constructing the final sets for training and testing. Different studies use a series of constraints on the aforementioned date fields to shrink the space of potential False Links. The literature [9,13,8] introduces various time constraints for commit dates. Mostly, the literature assumes [13,9,11] if an issue and a commit are related, they should have close submission dates (within one week). Hence, we used the same rule. However, there exist links that are more than seven days apart. Future research should devise better negative sampling techniques.

External Validity: External validity is concerned with the generalizability of the approach and results [29]. To increase the generalizability of our approach, we collected and assessed the performance of our approach on a set of 20 projects collected from three different studies in the field. The project goal and type vary from data processing frameworks to programming languages, deep learning APIs, and many more. Moreover, as different platforms provide different linking behavior, we included two combinations of issue tracking system (Jira) and version control system (Git) among the projects. The main programming language also varies for the selected projects. Note that LinkFormer achieves the lowest standard deviation in all settings indicating that its results are more stable across projects. As we focused on open-source projects, there is a potential threat that our findings can not be generalized to commercial projects. Although there are similarities in open source and commercial projects, companies’ policies may affect the commit practices. The impact of such decisions should be investigated in future research. To evaluate our generic model more fairly, we validate it using five folds and report both individual and the average scores. By breaking data into five smaller chunks and re-evaluating the model, we ensure that all of the data has been used for training and testing. Finally, our best model outperforms the baselines in at least 19 projects out of 20 projects in all settings. However, LinkFormer’s average scores are significantly higher in all settings than those of the baselines.
Construct Validity: Construct validity is concerned with the evaluation of the models [29]. Similar to previous work [9,11,12,7,10,13,8,30], we use the standard metric F1-measure commonly used in the literature as the harmonic mean of precision and recall scores to evaluate the performance of our approach against the state-of-the-art.

7 Conclusion

Automated linking of commits to their respective issue reports is commonly used to improve software maintenance tasks, such as software documentation, defect prediction, bug localization, software quality measurement, and more. In this work, we propose a new approach called LinkFormer and address three aspects of the link recovery problem, namely, accuracy, data leakage, and generalizability of the solution. We empirically showed the impact of train-test set splitting policies on the performance of models. Moreover, we train and evaluate two generic models in two transfer-learning settings and show that our proposed approach performs on par with the project-based setting. Future work can continue in this direction, focusing on building more generalizable models that are applicable to wider set of projects.

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Conflict of Interest

The authors have no conflict of interest.

Data Availability Statement

The dataset used for training the models and comparing approaches is publicly available online. [10]

[10] https://doi.org/10.5281/zenodo.6524460
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