CLCMiner: Detecting cross-language clones without intermediates

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SUMMARY   The proliferation of diverse kinds of programming languages and platforms makes it a common need to have the same functionality implemented in different languages for different platforms, such as Java for Android applications and C# for Windows phone applications. Although versions of code written in different languages appear syntactically quite different from each other, they are intended to implement the same software and typically contain many code snippets that implement similar functionalities, which we call cross-language clones. When the version of code in one language evolves according to changing functionality requirements and/or bug fixes, its cross-language clones may also need to be changed to maintain consistent implementations for the same functionality. Thus, it is needed to have automated ways to locate and track cross-language clones within the evolving software. In the literature, approaches for detecting cross-language clones are only for languages that share a common intermediate language (such as the .NET language family) because they are built on techniques for detecting single-language clones. To extend the capability of cross-language clone detection to more diverse kinds of languages, we propose a novel automated approach, CLCMiner, without the need of an intermediate language. It mines such clones from revision histories, based on our assumption that revisions to different versions of code implemented in different languages may naturally reflect how programmers change cross-language clones in practice, and that similarities among the revisions (referred to as clones in diffs or diff clones) may indicate actual similar code. We have implemented a prototype and applied it to ten open source projects implementations in both Java and C#. The reported clones that occur in revision histories are of high precision (89% on average) and recall (95% on average). Compared with token-based code clone detection tools that can treat code as plain texts, our tool can detect significantly more cross-language clones. All the evaluation results demonstrate the feasibility of revision-history based techniques for detecting cross-language clones without intermediates and point to promising future work.

key words: cross-language clone, code clone, revision, diff, similarity

1. Introduction

With diverse programming languages available on different platforms catering to varieties of users, it is a common need for the same functionality and even a whole software project to be implemented in different programming languages. A sample case is the availability of a mobile application that is implemented in three languages, Java for Android, C# for Windows phones and Objective-C for iPhones. Such re-implementations of a software project in different languages are also common for desktop applications. For example, Antlr [1], a parser generator, has versions implemented in Java, C#, JavaScript and Python. For another example, Lucene [2], a text search engine, has implementations in Java and C#. When implementing or changing a functionality in one version of such projects, it is naturally needed to change another version in a different language to maintain consistencies. It is also reasonable, in order to save coding efforts, for programmers to copy their modifications for one version into another version and adapt the copies to fit the different language. Even when the syntactic structures of two languages differ a lot, there should still be pieces of code in different languages having similar semantics for a similar functionality. As a result, projects in different languages can have similar code snippets in different programming languages too. In the literature [3], such code snippets are referred to as cross-language code clones.

Code clones may be considered harmful and removable [4] or useful and should be kept [5] depending on their usages. For cross-language clones, we take the view that they are often inevitable, and cannot be removed, based on our experiences and diverse landscape of available programming languages and platforms. Instead of removing clones, we thus need automated techniques to help programmers locate and maintain cross-language clones to save costs and improve developer productivity. For example, a developer D1 develops a cross-language project at the beginning, and later another developer D2, who is not so familiar with the source code takes over the project. When D2 modifies a code snippet in one programming language, all relevant code snippets in other languages may require similar modifications to maintain consistencies. In particular, when a bug is found and fixed in one programming language, D2 needs to check versions in other programming languages to fix similar bugs too. It would be rather tedious and error-prone for D2 to locate such cross-language clones manually, especially when their programming languages are quite different.

Many approaches have been proposed for detecting clones within one programming language [6–9]. A number of researchers [3, 10] have started to detect cross-language code clones too. However, their approaches are limited to
detect clones in the .NET language family that share a common intermediate language. In practice, many projects are implemented in other programming languages that may not be addressed by the existing approaches. Without a common intermediate language, we need to overcome the following challenges to detect cross-language clones:

**Challenge 1.** For different languages that do not share a common intermediate language, it is no longer feasible to reduce source code to an intermediate language and detect similar code based on the intermediates. We need to find a new way to represent code so that the similarity among code snippets can be measured.

**Challenge 2.** For different programming languages that have different grammars and APIs, it is much less likely to measure code similarity through syntactical structures, since even when code snippets in different programming languages implement the same functionality, their syntactical structures can be quite different. We need to find a code similarity measure that can be applied to code in different languages.

In short, we need design a language-agnostic way to represent code and measure code similarity for detecting clones across languages. In this paper, we propose a new approach, named CLCMiner, that can detect cross-language clones without intermediate languages. CLCMiner works by comparing revision histories recorded as diffs in software repositories. Here, diffs refers the change-log tool widely used in Version Control Systems (VCS) such as Git and SVN to identify the differences between files; a diff also refers to the differences produced by the diff tool.

The key assumption for our approach is that in multi-language projects, versions in different languages can have similar diffs since developers may need to change all versions in similar ways to implement the same functionalities in the versions. Also, when diffs are relatively small, the syntactic differences among diffs may not be that significant; instead, lexical appearances, such as identifier names, may give more hints whether two code snippets are implementing similar functionalities. Based on these intuitions, our approach detects cross-language clones by comparing the similarity among pieces of diffs in different languages and aligning each diff with the most similar one. We call this process **diff matching**. As a diff contains both the changed lines of code and their surrounding code, matched diffs make it easy to determine whether the involved lines are cross-language clones.

This paper makes the following contributions:

- To the best of our knowledge, we propose the first approach that detects cross-language clones for programming languages that do not have an intermediate language. Our approach is based on comparing code change histories, and thus reduces cross-language clone detection into a **diff matching** problem.
- We conduct an evaluation on 10 open source projects that have versions implemented in both Java and C#. Our results show that our approach achieves a high precision and recall. For the 10 projects, the average precision is 89.1% and the average recall is 95.0%.
- To improve our previous work [11], this paper introduces a sliding window into our diff matching algorithm and has increased the precision and recalls greatly.
- We further demonstrate the capability of **CLCMiner** for detecting significantly more cross-language clones by comparing it with token-based clone detection tools, **CCFinder** [7] and **ConQAT** [9], because those tools can treat code in different languages as plain texts and try to detect clones in plain texts.

Different from other clone detection techniques that aim to find all clones in a set of code, **CLCMiner** is designed to detect only clones in code that has ever been changed in the revision history (which are referred to as **diff clones** in this paper) because **CLCMiner** technically detects clones based on the **diffs**. Such clones may naturally overlap with each other or disappear along the project history in its latest version (Sections 4 and 5 will provide more statistics about **diff clones**). Despite the difference, detected clones in code change history can still help maintainers to understand the correspondence between code in different programming languages and facilitate many software engineering tasks that involve changing code clones, such as tracking and studying clone genealogies, refactoring code, detecting potential bugs from consistent and inconsistent clone changes [12–15].

The rest of this paper is organized as follows: Section 2 gives an example to illustrate the whole picture of our new idea. Section 3 presents the detail of our approach. Section 4 evaluates our approach. Section 5 discusses related issues. Section 6 presents related work. Section 7 concludes.
2. An Example

An example of two matched diffs in Java and C# code snippets is shown in Figure 1. The matched diff pair indicates a cross-language clone which has a similar functionality. The diff on the left-hand side records two lines of changes in an if-block in Java class MachineProbe, while the one on the right records four lines of changes in a block in C# class MachineProbe. This example is used to illustrate the problem and how our approach works. It is also used in the later part of the paper to explain the algorithm details.

In the example, both of the code snippets in the diffs intend to set the fields (i.e., line and charPositionInLine) of the object pointed to by the reference token. The Java code achieves this through invoking the object’s methods (i.e., setLine() and setCharPositionInLine()), while the C# code achieves this through assigning them directly. In addition, the Java jumps out of the if-block through a break statement, while the C# code uses a goto statement.

Our approach is able to detect cross-language clones from such diffs in Figure 1, since it reduces cross-language clone detection to a diff matching problem. It extracts all the diffs from the project (in both Java and C#), and matches each diff in Java code to a diff in C# code according to the filename without extension (e.g., MachineProbe) and the vocabulary similarity (e.g., the tokens of the identifier names and the words). The detailed algorithm to match the diffs will be presented in Section 3.

3. Approach and Implementation

The similar functionality implemented in different programming languages may diverge in the syntax, but the code snippet in one language (e.g. Java) can be used as a reference for implementation in another language (e.g., C#). As a result, similar variable or method names can be used in such cases. To detect cross-language clones, CLCMiner adopts Natural Language Precessing (NLP) techniques to calculate the similarity among pieces of diffs in different programming languages and selects the most similar one for each diff as a pair of matched diffs. Each pair of matched diffs refers to a pair of potential clones. Finally, CLCMiner ranks the matched pairs of diffs according to their diff similarity and reports top ones as cross-language clones.

Figure 2 shows the overview of CLCMiner. Each rectangle in blue represents a processing step, and each rounded rectangle in red represents an entity of each step. The input of CLCMiner is git logs, and its output is a ranked list of detected potential cross-language clones. The approach includes four main steps:

1. **Log Parsing.** This step extracts diffs and their attributes from revision logs.
2. **Normalizing.** This step normalizes diffs and prepares for the comparison in the next step.
3. **Diff Matching.** This step matches diffs in different languages by comparing their distance. For each diff, its matched one is the nearest one.
4. **Ranking & Reporting.** This step ranks matched diffs based on similarity and reports cross-language clones.

### 3.1 Log Parsing

In a Version Control System (VCS), repository logs record the evolution history information. For example, the structure of git logs is organized as follows: a git log consists of several commits; each commit is related to one or more files; each file is related to one or more diffs; each diff records one or more change hunks that occur in a code fragment [16].

Log parsing is a preparation process to extract useful information from repository logs. CLCMiner parses a repository log into a list of diffs and attaches each diff with a set of attributes, including commit date (CD), commit author (CA), commit ID (CID), filename (FN), and commit message (CM). For example, Table 1 lists the attributes of the diffs in Figure 1. Some attributes (e.g., FN) are useful for matching diffs, and others (e.g., CID) help to uniquely locate the code.

### 3.2 Normalizing

Normalizing is a process to remove uninteresting contents from the diffs and transform the rest into normalized comparison units. CLCMiner chooses the token streams of the diffs as the comparison unit, and normalizes the diffs into token streams as follows:

1. **Removing Comments.** To relieve the impact of the comments in natural language, CLCMiner first removes the comments from the code snippets in the diffs.
2. **Lexing.** CLCMiner lexes the code snippets in the diffs without comments into a token stream.
3. **Removing Punctuations.** Punctuations and numbers are removed from the token stream, as they often do not indicate significant semantics.
3.3 Diff Matching

Diff matching is a process to align a diff in a language (e.g., Java) to a diff in the other language (e.g., C#), according to their similarity. In our approach, we define a distance between diffs to measure their similarity.

3.3.1 Distance between Token Streams

Since the distance between diffs is based on the distance between their token streams, we first define the distance between token streams.

CLCMiner adopts Bag of Words (BOW) [17], a text representation technique widely used in NLP, which represents a piece of text as a bag of its words disregarding grammar and the ordering of words, to represent token streams as characteristic vectors. Each dimension of the characteristic vector denotes the number of a specific token in the token stream.

Fortwo vectors, \( V_i \) and the vector of token stream in \( V_j \), their distance is defined as follows:

\[
D_{ts}(V_i, V_j) = \frac{\sum_{k=1}^{n} |v_{ik} - v_{jk}|}{\sum_{k=1}^{n} (v_{ik} + v_{jk})} \tag{1}
\]

3.3.2 Distance between diffs

A straightforward way to calculate the distance between two diffs is to measure the distance between the two token streams of the diffs as we did previously [11]. However, we found in quite a few cases the length of two token streams are greatly different. As a result, the distance between the two token streams is so large that the two diffs are excluded from the clone reports. However, for these cases, the token stream of the shorter diff is in fact similar to a subsequence of the token stream of the longer one. It may help to detect more clones if we can measure the distance between subsequences of token streams. Thus, we improve our previous distance measurement by utilizing sliding windows to select a number of subsequences of token streams from the longer one to compare with the token stream for the shorter one.

CLCMiner sets the size of sliding window the same as the length of the shorter token stream and moves the sliding window along the longer token stream. Considering the accuracy, CLCMiner slides the sliding window one token per step. At each stop, a characteristic vector for the token stream in the sliding window is built. CLCMiner calculates the distance between it and the characteristic vector of the shorter token stream. Among all such calculated distances, the shortest distance is used as the distance between the two diffs. Formally, supposing diff \( d_1 \) and diff \( d_2 \) have \( m \) and \( n \) tokens in their own token streams respectively. If \( m > n \), the length of sliding window will be set as \( n \) and the sliding window will be moved along the token stream of \( d_1 \). Then, \( m - n + 1 \) characteristic vectors \( (V_{11}, V_{12}, \ldots, V_{1(m-n+1)}) \) of diff \( d_1 \) will be built. If \( m < n \), the length of sliding window will be set as \( m \) and the sliding window will be moved along the token stream of \( d_2 \). Then, \( n - m + 1 \) characteristic vectors \( (V_{21}, V_{22}, \ldots, V_{2(n-m+1)}) \) will be built. If \( m = n \), there will be no sliding window. In brief, the distance between diffs \( d_1 \) and \( d_2 \) is defined as follows:

\[
D_d(d_1, d_2) = \begin{cases} 
\min_{1 \leq i \leq m-n+1} D_{ts}(V_i, V_{2i}) & m > n \\
D_{ts}(V_i, V_{2i}) & m = n \\
\min_{1 \leq i \leq n-m+1} D_{ts}(V_i, V_{2i}) & m < n 
\end{cases} \tag{2}
\]

For the example in Section 2, the lengths of Java and C# token streams (in Table 1) are 80 and 59 respectively. Therefore, the length of sliding window is 59 as the C# one. CLCMiner moves the sliding window along the Java token stream, builds characteristic vector for each token stream in the sliding window. When the sliding window stop at the end of the Java token stream (the sliding windows contains the underlined tokens in Table 1), it has the shortest distance with the C# one. Table 2 shows the characteristic vectors, which have the shortest distances. Column “Token” lists the words appearing in the token streams. Columns “\( V_i \)” and “\( V_j \)” list the vector of token stream in the sliding window in MachineProbe.java and the vector of token stream in MachineProbe.cs respectively. Column “\( |V_i - V_j| \)” lists the absolute value of the difference between the values of the corresponding dimension of the vectors. For example, token “break” appears in the sliding window of the Java token stream but does not appear in the C# one, and the difference is 1 (\(|1 - 0|\)). In this way, the distance between two diffs is 0.305 (36/(59 + 59)).

3.3.3 Matching Algorithm

Algorithm 1 shows the details for matching diffs. It takes as input two lists of diffs. The output is a list of matched diff pairs, each of which is from different input lists. CLCMiner compares the sizes of the two diff lists and sets the smaller one and the larger one as source and target respectively (Lines 1–2). The diffs, whose file names are the same (filename extensions are ignored), are called neigh-

| Token | \( V_i \) | \( V_j \) | \( |V_i - V_j| \) |
|-------|--------|--------|----------------|
| ab    | 1      | 1      | 0              |
| ad    | 1      | 0      | 1              |
| associated | 2 | 1 | 1 |
| break | 1 | 0 | 1 |
| break | 1 | 0 | 1 |
| tokens | 3 | 7 | 4 |
| total | 40 | 59 | 10 |
bors of each other. For each `diff` in `source` (`d_s`), `CLCMiner` searches in `target` for its nearest neighbors by comparing the distances from `d_s` to all of its neighbors in `target` (Lines 3–18). The shortest distance indicates the nearest one. As long as there exists a neighbor in `target` for `d_s`, `d_s` can be matched; otherwise, it cannot.

For projects that have multiple implementations in different languages, code in one language is often used as a reference for the implementation in another language and the same functionality is likely to be encapsulated in a file with the same name, especially for object-oriented languages (e.g., Java and C#). With this heuristic, `CLCMiner` only matches a `diff` with its neighbors having the same file name.

`CLCMiner` by default only matches a `diff` to its nearest neighbor to report a clone pair (or clone pairs if there are more than one nearest neighbors having the same shortest distance), instead of reporting all its top-k nearest neighbors to form a clone group. This takes into consideration that, with the nearest neighbor, the other top-k nearest neighbors and even clones in files with different names can be detected by a single-language clone detector to build more comprehensive clone groups.

3.4 Ranking and Reporting

For each pair of matched `diffs`, the code fragments can be located via their attributes (e.g., FN and CID). These pairs of code fragments are considered as potential clones, which are called `clone candidates`. `CLCMiner` ranks all such pairs according to their `diff` distances. The pairs whose `diff` distances are lower than a distance threshold are to be reported as clones. The distance threshold is empirically determined, which will be explained in detail in Section 4.1.

4. Evaluation

In order to justify the effectiveness of `CLCMiner` in detecting clones in code change history and in comparison with related work, we perform empirical evaluation to answer the following research questions:

- **RQ 1.** How accurate is `CLCMiner`? How do sliding windows help improve `CLCMiner` accuracy?
- **RQ 2.** How effectively does `CLCMiner` detect cross-language clones compared with other token-based clone detection tools that may detect cross-language clones by treating code as plain texts?
- **RQ 3.** What is the impact of the other code-related attributes on cross-language clones?

### 4.1 RQ1. Accuracy

With respect to the previous version of `CLCMiner` that does not use sliding windows [11], we further evaluate the accuracy of the improved `CLCMiner` for more projects with sliding windows. In the paper, `CLCMiner` detects cross-language clones from 10 open source projects implemented in both Java and C#. For each project, `CLCMiner` reports a ranked list of cross-language clone pairs.

#### 4.1.1 Setup

Table 3 shows the projects and lines of code (LOCs without comments in the latest revision), numbers of revisions, log sizes, numbers of commits and numbers of `diffs`. Column “#Cand.” lists the numbers of clone candidates, which are the numbers of matched `diff` pairs. Since some `diffs` have more than one nearest neighbors, the number of matched `diff` pairs may be greater than the number of `diffs`. Due to the large number of clone candidates and limited manpower, we randomly sampled, in a uniform way, a small percentage of the candidates in the ranked lists (cf. Column “#Spl”).

Two co-authors manually labelled whether they were actual clones separately based on the clone definition of Bellon [18] and the functionality equivalence. If there exists a difference between the labels given by them, it will be labelled and decided by a third co-author. We calculated the clone ratio and its distribution `w.r.t. the distances, where the clone ratio is defined as \( CR = \frac{\#clones}{\#candidates} \times 100\% \).
4.1.2 Result

Figure 3 shows the clone ratio distribution and the accumulated clone ratio w.r.t. the diff distances calculated by the algorithm with sliding window. The clone ratio distribution in Figure 3(a) indicates:

- almost all the candidates whose diff distance is lower than 0.3 are clones;
- almost none of the candidates whose diff distance is larger than 0.7 is clone;
- with the distance increasing from 0.3 to 0.5, the clone ratio decreases gradually;
- with the distance increasing from 0.5 to 0.7, the clone ratio decreases greatly.

The accumulated clone ratio in Figure 3(b) also decreases with the increasing of the diff distance. Intuitively, when the diff distance is lower than 0.5, the clone ratio decreases slowly and when the diff distance is larger than 0.5, the clone ratio decreases greatly.

In order to choose a threshold distance to determine cross-language clones, we plot a Receiver Operating Characteristic (ROC) curve for the 10 projects in Figure 4. The curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings. The slope (k) of the curve reflects the relative increasing speed between TPR and FPR w.r.t the increase of threshold setting value: k > 1 means TPR increases more greatly than FPR; k < 1 means FPR increases more greatly than TPR.

In Figure 4, the black solid curve is the average ROC curve of the ten projects, the red dashed one is the best one (i.e., Lucene) among them and the orange dotted one is the worst one (i.e., ua-parser) among them. We can find that the slope of the curve decreases with the increase of TPR and FPR. We can see for all of them the slope decreases w.r.t. the increase of threshold setting value. When the slope is around 1, the corresponding threshold is the proper threshold. In our experiment, it is 0.5. If the diff distance is lower than 0.5, its related clone candidate is considered as a clone; if the diff distance is larger than 0.5, its related clone candidate is not considered as a clone.

In this experiment, we use precision and recall to measure the accuracy of CLCMiner. For the distance threshold 0.5, CLCMiner reports as clones the pairs of code fragments in the ranked list whose diff distance is lower than 0.5. In this way, the precision and recall are defined as follows:

\[
\text{precision} = \frac{TP_{d \leq 0.5}}{TP_{d \leq 0.5} + FP_{d \leq 0.5}} \tag{3}
\]

\[
\text{recall} = \frac{TP_{d \leq 0.5}}{TP_{d \leq 1.0}} \tag{4}
\]

Since it is unknown how many actual cross-language clones in the projects, we use the “relative” recall (Equation (4)) to reflect the capability that CLCMiner detect cross-language clones from the repository logs. The precision and recall for the 10 projects are listed in Table 4. The average precision and recall are 89.1% and 95.0% respectively.

Previously [11], CLCMiner does not use sliding window and is evaluated on projects Antlr, FpML, Log4j/Log4net, Lucene and Spring. The precision and recall are listed in Column “No Sliding Window” in Table 5. Column “Sliding Window” lists the corresponding precision and recall with sliding window. We can see that with the sliding window, the average precision is improved greatly from 87.4% to 96.1% and the recall is improved from 93.2% to 93.6%.

4.1.3 Discussion

The results in Table 5 show CLCMiner with sliding windows always achieves higher recall (i.e., detecting more clones) than without. In terms of precisions, most results with sliding windows also happen to be higher, except one case for the project Log4j/Log4net. We investigate more clone candidates in Log4j/Log4net manually, and find that there do exist many diff pairs whose token streams are greatly different; using sliding windows helps to reduce the calculated distance among various subsequences of the token streams, leading to many more reported clone pairs within the similarity threshold. However, those similar subsequences are significantly
smaller than the whole token streams and are not sufficient in determining whether the whole token streams are similar, leading to more false positives in our reports sometime.

4.2 RQ2. Comparison with Token-Based Clone Detection

The existing clone detection tools aim at single-language clones, but a few token-based clone detection tools [19] can treat inputs as plaintexts without language-specific lexical or syntactical information to detect some cross-language clones (e.g., ConQAT [7] and ConQAT [9]). In this experiment, we compare CLCMiner with CCFinder and ConQAT.

4.2.1 Setup

We set all the diffs of 10 projects as the input for the clone detection tools and compare the cross-language clones that they detect from the diffs. We configure the tools as follows:

**CLCMiner.** The threshold distance of CLCMiner is set as 0.5. CLCMiner is set to report a diff and its neighbor as a clone pair if their diff distance is equal to or less than 0.5 no matter whether the neighbor is the nearest one or not. To speed up the diff matching, CLCMiner is set to slide the sliding window 10 tokens per step.

**CCFinder.** The arguments of CCFinder are set as default. That is the minimum number of tokens is 50 and that the minimum number of kinds of tokens in code fragments (metric TKS) is 12. The diffs are divided into two groups (i.e., Java group and C# group). CCFinder is set to detect code clones between diffs from the distinct diff groups but not to detect code clones between diffs in the same group.

**ConQAT.** The gapped ratio of ConQAT is set as 0.2, which can make the number of clones reported is twice as that when the gapped ratio is set as 0. The minimum number is set as 5 and the max errors are set as 3. Instead of clone pairs, ConQAT reports clone groups, which may include more than two diffs. In order to facilitate the comparison, we separate each clone group into clone pairs, in which one is a Java diff and the other is C# one.

In addition, we run CCFinder and ConQAT to detect cross-language clones from files having the same name only as CLCMiner does (cf. Line 6 in Algorithm 1).

4.2.2 Result

Table 6 lists the number of cross-language clones reported by each tool. We can see that totally CLCMiner can detect 1,403,069 pairs of cross-language clones from the 10 projects, while CCFinder and ConQAT can detect 10,153 and 93,833 pairs respectively. Note that the numbers of the reported clone pairs are much larger than that of the diffs because, based on the above tool configurations, each diff may appear in more than one clone pair.

The number of clone pairs reported by both CLCMiner and CCFinder (\(\cap_{12}\)) is 9,730, which means 9,730 out of 10,153 (95.8%) clones reported by CCFinder are also reported by CLCMiner. The number of clone pairs reported by both CLCMiner and ConQAT (\(\cap_{13}\)) is 91,244, which means 91,244 out of 93,833 (97.2%) clones reported by ConQAT are also reported by CLCMiner. The number of clone pairs reported by both CCFinder and ConQAT (\(\cap_{23}\)) is 5,463 and the number of clone pairs reported by all the three tools (\(\cap_{123}\)) is 5,418, which means 5,418 out of 5,463 (99.1%) of clone pairs reported both by CCFinder and ConQAT are also reported by CLCMiner. The result indicates that CLCMiner can detect the cross-language clones in the diffs effectively.

4.2.3 Discussion

Why does CLCMiner detect more cross-language clones? Token-based single-language clone detection tools lex each line of source files into token sequence and utilizes certain string matching algorithm to search for similar subsequences, while CLCMiner splits each camel case identifier (e.g., variable names and method names) and utilizes the statistical method to calculate the distance between diffs and search for similar diffs. In this way, CLCMiner does finer grained comparison than these tools.

Although CLCMiner can detect most of the ones reported by CCFinder and ConQAT, some are still missed by CLCMiner. We investigate those clones missed by CLCMiner and summarize potential causes as follows:

- Since the sizes of our sliding windows are fixed to be the same as the shorter of the two diff token streams, CLCMiner can miss clones that are only a small part of the two diffs. On the contrary, CCFinder and ConQAT are able to report any subsequences of the token stream as clones as long as they are bigger than the minimum number of tokens required.
- CLCMiner uses the distance threshold 0.5 to report potential clones; it will miss cross-language clones whose distances are large than 0.5 (cf. Figures 3 and 4). CCFinder and ConQAT may be able to catch some of the CLCMiner’s false negatives.
- For performance issues, our sliding windows are moved forward 10 tokens at each step, which may miss the shortest distance that should have been less than 0.5.
4.3 RQ3. Impact of More Attributes of Diffs

For matching diffs, BOW as used in Section 3.3.2 may not be the only choice. We identify the following attributes that may have an impact on the similarity among diffs too: commit author (CA), commit date (CD), and commit message (CM) of the diffs. In this subsection, based on the sampled and labelled clone candidates, we analyze the potential impact of these attributes and discuss how to improve the effectiveness of matching cross-language clones in future work.

4.3.1 Setup

Intuitively, the attributes CA, CD and CM of diffs tend to have some correlations with the diff similarity. As a developer may have a programming style that may persist even across different languages, a pair of similar diffs from different language versions of a project may be more likely to be committed by the same developer. As the functionalities in different language versions of a project are likely to remain consistent, changes in one language version may induce similar changes in another within a short interval. As a commit message often summarizes the changes in the commit, a pair of similar diffs may be more likely to share similar commit messages. Based on the intuitions, here we aim to test the (in)validity of our null hypotheses as follows:

- \( H_{d0} \): Similar diffs and dissimilar diffs have the same probability to be committed by the same author.
- \( H_{d1} \): The interval between the commit dates of similar diffs is likely to be as long as that of dissimilar ones.
- \( H_{m0} \): The distances between the commit messages of the similar diffs is likely to be as large as that of the dissimilar ones.

To investigate these hypotheses, we look into the labels for the clone reports of the 10 projects sampled in the way mentioned in Section 4.1.1. For each hypothesis, we build two variables: one is a label \( l \) indicating whether the diffs are similar, and the other is the value of the corresponding attribute (\( ca, cd \) or \( cm \)). For variable \( l \), \( l = 1 \) means the pair of diffs is similar and \( l = 0 \) means it is not. For variable \( ca, ca = 1 \) means the pair of diffs is committed by the same author and \( ca = 0 \) mean it is not. Variable \( cd \) is the interval between the commit dates of two diffs. Variable \( cm \) is the distance between commit messages of two diffs.

4.3.2 Result

Table 7 lists the \( t \)-test statistics of the three hypotheses. Based on the \( t \)-statistic for each hypothesis, all the null hypotheses are rejected (\( p \)-value < 0.0001). This means the attribute CA, CD, CM have some correlation ship with the similarity of their corresponding \( diff \) pair.

We find that about 29.6% pairs of similar diffs are committed by the same author, but only 7.7% pairs of dissimilar diffs are committed by the same author. Therefore, pairs of similar diffs tend to be committed by the same author. For \( H_{d0} \), pairs of similar diffs are committed 585 days after one another on average, while pairs of dissimilar diffs are committed 790 days after one another on average. Therefore, similar diffs tend to be committed between a shorter period of time. For \( H_{m0} \), the distances between the commit messages of similar diffs tend to be shorter.

In addition, the Pearson’s correlation coefficient between \( l \) and \( ca \) is 0.28, which indicates that the diffs committed by the same author are more likely to be clones than those committed by different authors. The coefficient between \( l \) and \( cd \) is -0.14, which indicates that diffs committed between a shorter period of time are more likely to be clones than those committed between a longer period of time. The coefficient between \( l \) and \( cm \) is -0.31, which indicates that diffs with similar commit messages are more likely to be clones than those with dissimilar commit messages.

4.3.3 Discussion

The above statistics are aggregated from 10 projects which can differ from one to another. The correlations between the attributes and the diff similarity are weak, indicating none of the attributes is a deciding factor for \( diff \) pairs to be clones. Whether a \( diff \) pair is clones could be a combined effect of all the attributes and even some contexts beyond \( diff \) itself.

In our future work, we plan to investigate whether the combination of more attributes, together with additional ones discussed in Section 5, can be used to improve cross-language clone detection in code change histories.

5. Discussion and Future Work

We realize that our approach is subject to various threats to validity in its algorithm design, experimental settings, and generalizability. In the following, we discuss several of such threats and propose possible mitigations.
Mapping clones in change histories to the latest revision. Since CLCMiner detects clones in diffs and the code corresponding to some of the diff clones may be changed repeatedly or even deleted along software evolution, it will cause some deleted code to be reported as clones or the same piece of code to be reported repeatedly in many different diff clone pairs. On one hand, clones occurred repeatedly or deleted in history may still be useful for the purpose of studying code evolution, refactoring, and consistency (e.g., [12–15]); on the other hand, developers working on the latest revision of a project may not need deleted or overlapping clones, and removing such clones from the clone reports can improve the usefulness of CLCMiner for such developers. To address the concern on different use cases for diff clones, we further track them to check whether they still exist in the latest revision. We compare the historical file containing each diff clone with the file in the latest revision, by the diff tool, to build an existence mapping for all lines of code in the diff clone. Based on the mapping, we classify diff clones into 5 categories: 1) the clones whose containing files no longer exist in the latest revision (NF); 2) the clones none of whose lines of code exists in the latest revision (R_1); 3) the clones less than 50% of whose lines of code are still in the latest revision (R_2); 4) the clones over 50% but not all of whose lines of code are still in the latest revision (R_3); 5) the clones all of whose lines of code are still in the latest revision (R_4).

We categorize all the clones reported in Table 6 into Table 8. It shows that, along software evolution, on average 65.8% (NF and R_1) of the diff clones no longer exist in the latest revision, while 34.2% (R_2, R_3 and R_4) still exist or partially exist. In particular, over 50% of lines of code in 7% (R_3 and R_4) of the diff clones still exist.

Furthermore, totally the 10 projects have 3,602,358 lines in their latest revisions (including comments), 805,960 (about 22.4%) of which can be mapped from diff clones, which may be used as an alternative way to detect missing clones in the latest revisions. Column “LR LOC” shows the number of lines in the latest revision that can be mapped from at least one diff clone, and Column “DC LOC” shows the total number of lines from the diff clones in R_2, R_3 and R_4. We use the ratio (OR=“DC LOC”/“LR LOC”) as an estimate for the average number of reported diff clones (6.3 on average) that overlap with each clone pair mapped to the latest revision.

In brief, many of detected diff clones remain and can help find similar code in different programming languages in the latest revisions; many others are deleted or overlapped with others, but can be useful for tasks related clone changes.

Using comments in code. In diff normalization (Section 3.2), code comments were removed as we hypothesized that comments in natural language may be too high-level and appear similar even for non-clones and thus are not accurate enough for clone detection. However, during the manual labelling of the sampled diff pair reports, we noticed that many clone pairs either contain quite different comments for different parts of the two code fragments in the pair or contain almost exactly the same comments (which may indicate an actual copying-pasting operation). In our future work, we plan to more systematically investigate how comments in code are related with clones.

Relaxing filenames. Diff matching (Section 3.3.2) used a requirement that potentially matched diffs should be from files of the same name, and thus all code in every reported clone pair has the same file name. However, cross-language clones can appear in files with different names, especially if they are from different projects. The setting was added based on the heuristic that implementations of similar functionalities in different languages within the same project are likely to be in files of the same name and to reduce the pair-wise comparison time for projects involving too many commits; it is a trade-off between detection efficiency and recall. In the future work, we will optimize our matching algorithm and analyze how the file names impact cross-language clones that may be from different projects.

Detecting clone groups and change propagation. CLCMiner matches a diff in one language to its nearest neighbors in another language only, as we focus on the feasibility of using diffs for detecting cross-language clones. We can change the setting to return all the neighbors of a diff whose distance is within a small threshold, which can enable us to detect cross-language clone groups, in addition to pairs. Also, by linking clone groups based on clone transitivity within a threshold and complemented with a single-language detector, we will be able to study how changes are propagated even through different languages, extending similar studies within the same language [20].

Detecting clones beyond revision histories. CLCMiner is based on revision histories; it is limited to detect cross-language clones that have been changed in the past in the same project. For clones that are never changed, we can explore more language attributes that can identify clone relations (e.g., using deep learning to build vector representation of programs [21]) across languages. We also believe this limitation can be compensated by a single-language detector that can detect cross-project and same-language clones based on certain clone transitivity across projects and languages.

Crossing more languages. Increasing demands for cross-platform mobile applications (e.g., iOS and Android) raise the need for quick development that can reuse code across more diverse kinds of languages (e.g., Objective-C, Swift, and Java). Since functionalities implemented in one programming language can be used as a reference for the

| Projects | NF | R_1 | R_2 | R_3 | R_4 | LR LOC | DC LOC | OR |
|----------|----|-----|-----|-----|-----|--------|--------|----|
| Ave      | 2.4 | 0.7 | 49.1 | 12.3 | 15.4 | 55,285 | 198,649 | 3.6 |
| chandra   | 100% | 0 | 0 | 0 | 0 | 0 | 0 | NA |
| DataStar  | 23.3% | 9.2% | 36.2% | 7.1% | 13.9% | 14,889 | 96,332 | 6.4 |
| Faisal    | 5.9% | 2.5% | 18.9% | 9.3% | 3.9% | 4,096 | 11,849 | 3.5 |
| FDMC      | 22.3% | 2.3% | 30.9% | 19.7% | 10.6% | 58,124 | 249,839 | 4.5 |
| Log4jNet  | 26.9% | 3.6% | 31.8% | 32.9% | 1.4% | 22,160 | 114,209 | 5.2 |
| Eclizer   | 40.9% | 32.1% | 25.4% | 2.9% | 3.7% | 570,582 | 3,044,085 | 5.0 |
| Spring    | 55.9% | 3.5% | 26.8% | 10.2% | 1.8% | 65,387 | 145,958 | 5.3 |
| tra-pars  | 100% | 0 | 0 | 0 | 0 | 0 | 0 | NA |
| Ave       | 32.2% | 27.2% | 24.9% | 4.9% | 2.1% | 805,960 | 5,100,601 | 6.1 |

NF: No Files; R_1: (0, 50%); R_2: (0, 50%); R_3: [50%, 100%]; R_4: [100%, 100%];
implementation in another language, code fragments implementing similar functionalities in different languages would be changed in a similar way. We believe there exist some alignments between the changed code as long as the changes in different languages use similar lexical features, such as identifier names. In our future work, we plan to adapt CLCMiner to more languages and explore more attributes that can identify similar changes and be used to detect clones and facilitate code reuse across different languages.

Handling false positives. Although the precisions of the results reported by CLCMiner are relatively high, there is still space for improvement. We investigated the false positives and found they may have various characteristics causing “accidental similarity” among diffs: 1) a short method is defined in one diff but invoked in the other diff; 2) the diffs contain code that handles exceptions or errors; 3) the diffs contain a number of same string constants used differently; 4) the diffs contain a number of different numeric values which were excluded by our normalizing step; 5) the diffs contain code that uses the same set of library functions (e.g., File I/O, Http-Headers) in different ways. In our future work, we will refine CLCMiner to handle such cases.

6. Related Work

Cross-language clone detection. The number of various software systems implemented in multiple languages is increasing considerably [22], but cross-language clone detection is limited. Kraft et al. [3] conduct the first study on code clones that span over multiple languages. They implemented a tool called C2D2 based on the CodeDOM library in the Microsoft .NET framework, which uses NRefactory Library to generate the Unified CodeDOM graph for both C# and VB.NET. Al-omari et al. [10] present a clone detection approach for the .NET language family too, based on the Common Intermediate Language (CIL). It can detect cross-language clone pairs in C#, Java, and VB.NET. Compared with these work, our approach focuses on detecting cross-language clone detection on different platforms without common intermediate languages. Nakamura et al. [23] detect interlanguage clones that are clones whose code may be in more than one programming languages (e.g., a web page containing both HTML and Javascript), while each of our cross-language clones is still code in one language only.

Vocabulary similarity. Vocabulary similarity is an efficient way for semantic similarity. Marcus et al. [24] apply Latent Semantic Indexing (LSI) to source code and its associated internal documentation (e.g., comments) and could detect high-level concept clones with low costs. Kuhn et al. [25] introduce Semantic Clustering, which is also based on LSI to group source artifacts that use similar vocabulary. Semantic clustering captures topics regardless of class hierarchies, packages, and other structures. Lucia et al. [26] leverage information retrieval techniques such as VSM, LSI, and LDA to pick terms from specific parts of source code and comments for source code labeling. They can efficiently identify and cluster topics in the source code. Since it is difficult to analyze diffs for different programming languages by traditional program analysis tools, our approach applied vocabulary similarity to measure the diff similarity.

Data mining in VCS. There are considerable studies of data mining in Version Control Systems (VCS). Zimmermann et al. [27] apply data mining on version histories to recommend related syntactic changes. Girba et al. [28] apply concept analysis on VCS to identify groups of co-changes. McIntosh, et al. [29] mine source and test code for accompanying build changes. We apply data mining on VCS for a different purpose, detecting cross-language clones.

7. Conclusion

This paper proposes a novel approach, CLCMiner, that detects cross-language clones without common intermediate languages. Our key new idea is to utilize diff similarity. We have implemented and evaluated its prototype on 10 open source projects. The results show that our approach can detect many cross-language code clones that appear in diffs in the revision histories with a high precision of 89.1% and a high recall 95% on average.

To improve CLCMiner in our future work, we plan to refine the handling of false positives, detect more cross-language clones not captured in revision histories by incorporating in single-language clone detectors, and detect more clone groups across more languages (e.g., Objective-C, Swift, and Java) as described in Section 5.

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