Multi-Objective Optimization for Token-Based Clone Detection

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ABSTRACT

Clone detection plays an important role in software engineering. Finding clones within a single project introduces possible refactoring opportunities, and between different projects it could be used for detecting code reuse or possible licensing violations.

In this paper, we propose a modification to token-based clone detection that allows detecting more clone pairs of greater diversity without losing precision by implementing multi-parameter search, i.e. conducting the search several times, aimed at different groups of clones. To combat the increase in operation time that this approach brings about, we propose an optimization that allows to significantly decrease the overlap in detected clones between the searches. The method is applicable to any clone detector tool that uses tokens and similarity measures, highly configurable and can also be run in parallel, making it well-suited for large-scale analysis research. We describe the method and its optimization and evaluate them with two different popular clone detection tools on two datasets of different sizes, consisting of four prominent open source projects. The implementation of the technique allows to increase the number of detected clones by 41.9–52.7% for different datasets. We discuss the results and consider further research possibilities.

1 INTRODUCTION

When two pieces of code are the same or are similar to each other, they are called clones. Several studies have shown that a significant part of modern software code consists of clones [2, 16, 21]. Detection of such clones is an important problem in software engineering that has been significantly developed in the last decades.

Clone detection tasks can be divided into two large categories: intra-project clone detection and inter-project clone detection.

The first category deals with clones inside of a single project that are introduced when a user simply copies and pastes their own code or creates a lot of similar pieces of code with slight modifications. Such clones make the maintaining of the project more difficult, for example, due to the copying of buggy code. Research has shown that maintaining cloned bugs presents serious challenges, and at the same time, providing the users with the information about clones in the code can significantly increase the efficiency of bug detection and fixing [3–5, 17]. In general, it is preferable to have as few unnecessary code clones in a project as possible, because it can be difficult to change them all simultaneously. Detecting clones within a project can allow the developers to better optimize their software, decrease its spread, and prevent future bugs by uniting fragments of code with similar functionality.

Inter-project clone detection involves searching for clones between different projects or systems. Inter-project clones are relevant for detecting plagiarism and license violations [10, 24], identifying potential library candidates from the most used pieces of code [11], detecting similar mobile applications [6], etc.

A lot of popular tools perform token-based clone detection, meaning that pieces of code are compared as bags of tokens. This approach is simple, as it does not require the understanding of the semantics of the code, and it also scales well, because bags of tokens can be compared in many different ways and a lot of heuristics can be applied to decrease the operation time of the process. The latter is very important, because scalability is a prerequisite in many clone detection tasks: very often, clone detection is performed on large datasets of millions of lines of code, for example, in plagiarism detection.

In this paper, we propose a modification to token-based clone detection that consists in implementing the search with a parametric curve, i.e. a set of different parameter configurations aimed at different groups of clones that allows to detect a larger amount of diverse clones. Determining these configurations constitutes carrying out multi-objective optimization for the task of detecting valid clone pairs. The varied parameters in our technique are the similarity threshold and the length of pieces of code in tokens. This approach allows researchers to find more clones of various kind without losing precision by merging results from these different clone detection runs. The method can be applied to any token-based clone detection tool, can be widely configured and is well-suited for
large-scale analysis that requires a single case of clone detection. The approach allows to detect larger and somewhat less similar clone pairs that are often of interest: within a single system, the presence of such pieces of code might indicate the need for refactoring, whereas between systems, larger blocks are of special interest, since they often contain significant sub-block similarities and can be more scrupulously checked for possible violations.

We also propose an optimization to this technique that allows to decrease the overlap in discovered clones and therefore to decrease the method’s operation time. The optimization consists in estimating the most extreme cases of possible blocks sizes in a clone pair and excluding pairs that are guaranteed to be discovered in another search.

Our contributions are the following:

- We propose the technique for increasing the amount of found clones in token-based clone detection without decreasing its precision. The method is based on merging results from separate clone detection runs with different parameters aimed at different groups of clones, where each parameter configuration is labeled for a desired precision.
- We implement the proposed approach and estimate the necessary parameter configurations for two prominent clone detection tools that can present code in the form of tokens, SourcererCC [23] and CloneWorks [28].
- We evaluate the method using the clone detection tools on two datasets consisting of four prominent open-source repositories. For a smaller dataset, the technique demonstrates an increase in the amount of detected clone pairs of 41.9% for SourcererCC and 52.7% for CloneWorks. For a larger dataset it demonstrates an increase of 45.9% for SourcererCC and 44.1% for CloneWorks.
- We propose an optimization to this method that consists of minimizing the amount of overlapping detected clones. For instance, in the case of a clone detection with SourcererCC on a larger dataset with implementing a parametric curve, the optimization decreased the operation time of the technique by 20.1%, making a total of eight runs only 2.5 times slower than performing a clone detection with a single parameters configuration.

The remainder of the paper is organized as follows. In Section 2 we give deeper insight into the problem of clone detection, the specifics of token-based clone detection techniques and various heuristics that are used in these methods. Section 3 describes the proposed method and its optimization in details, in Section 4 we estimate the necessary parameters configurations for the technique, in Section 5 we evaluate the method and discuss the results. Section 6 discusses possible threats to validity of the research, and in Section 7 we summarize the study and describe our future plans.

2 BACKGROUND

2.1 Clone detection

Code clones are traditionally divided into four types [20]. Exact clones (Type-1) are identical code fragments except for whitespaces, layouts, and comments. Renamed clones (Type-2) might also differ in identifiers, types, and literals. Together with Type-1 clones, these code clones constitute the most basic and straightforward definition of a clone. Presence of such pieces of code within a project indicates a strong possibility of a need in refactoring, and for non-trivial code pieces this might also constitute code borrowing between systems that can be checked for possible licensing violations. Near-miss clones (Type-3) are subjected to more significant modifications like adding, removing, or moving specific statements, which still produce a similar outcome. Finally, semantic clones (Type-4) are pieces of code that are similar functionally but use different syntactic variants. These pieces of code are not usually a product of copying, since they are so different, and therefore usually cannot be considered duplicate, however, their detection presents interest in researching the variability of certain tasks in software engineering and categorizing their implementations. Within such strong syntactic deviations, it is even possible to detect code clones between different programming languages [15].

Every type of clones requires their own detection tool: a lot of tools draw the line between Type-2 and Type-3 clones, a lot of tools support Type-3 clones, and certain specific tools are aimed at detecting Type-4 clones. In general, proposed techniques differ in the method of code representations and the comparison method. Source code can be represented as lines of code, tokens, abstract syntax trees, etc., and its units (lines, bags of tokens, sub-trees, respectively) can be compared using various metrics. A recent comprehensive review of clone detection approaches and tools [1] lists six main categories of techniques: textual, lexical, tree-based, metric-based, semantic, and hybrid.

Textual approaches [14, 31] perceive code as a sequence of lines or strings that are compared to each other to determine clone pairs. Lexical approaches [13, 23], also known as token-based, transform source code into a sequence of tokens, after which this sequence is scanned for duplicate subsequences and they are returned as clones. In tree-based detection techniques [7, 12], the code is parsed into an abstract syntax tree or a parsing tree, after which an algorithm searches for matching sub-trees. Metric-based approaches [27, 28] apply various similarity metrics to syntactic units of code like classes or functions, and compare these metrics to detect possible clones. Both tree-based and metric-based techniques often employ machine learning algorithms. In semantic approaches [8, 29], programs are often represented as program dependency graphs, carrying control flow and data flow information, allowing these methods to work with semantic information about the code. The last category, hybrid approaches [25, 26], includes various techniques that use several of these approaches or a combination of them.

Different clone detection approaches have different advantages and disadvantages. Token-based techniques, despite being on the simpler end of the spectrum, are still very popular and widely used. Their main disadvantage is the inability to detect Type-4 clones. However, not every clone detection task is aimed at detecting Type-4 clones (for example, certain plagiarism and license violation analysis is not). The main reason token-based clone detection tools are widespread is their good scaling, which makes them uniquely qualified for extremely large datasets of millions lines of code.
2.2 Token-based clone detection

The general pipeline of token-based clone detection consists of two stages: tokenization and clone detection itself. In the first part, the source code is parsed into blocks and represented as a sequence of tokens. Blocks are units of code that are being compared. Different granularity levels are possible: blocks can represent methods, functions, classes, files, depending on the specific task at hand. Various methods might implement their own definition of tokens, but the definition of Sajnani et al. [23] is a common one: tokens are defined as programming language keywords, literals, and identifiers. As a result of tokenization, the code is represented as a list of blocks, each of which is, in turn, represented as a list of tokens.

In the clone detection stage, pairs of blocks are compared to each other by comparing their lists of tokens using a certain similarity function that produces the similarity of pairs. In order to be considered clones, this similarity must be larger than a certain Similarity Threshold $\theta$. In the simplest and most popular case, the Similarity Threshold is the amount of tokens that the blocks must share. Additionally, one can specify Lower Token Length Threshold and Upper Token Length Threshold, which narrows down the range of blocks of interest in size. The latter is rarely used, but the Lower Token Length Threshold is used constantly to filter out the most trivial and universal pieces of code. Even if a certain token-based clone detection tool does not natively support Token Length filtering, it is possible to add a preprocessing stage and exclude all the blocks outside of the desired range.

In the recent years, token-based clone detection has come a long way and various heuristics and improvements were introduced that work towards decreasing the operation time of the algorithms without losing valid clone pairs. One of the most popular token-based clone detectors that consistently shows good results is SourcererCC [23], which uses inverted index to query the potential clones of Types 1, 2, and 3, and achieves high scalability by implementing two filtering heuristics of the clone detection process.

The first heuristic is prefix filtering, which is used to significantly decrease the amount of fully processed pairs. The idea of this filtering is that when two sets have a large overlap, their smaller subsets will also overlap. For every block, consisting of a sorted list of tokens, a prefix is defined as a sub-block consisting of $|t| - \left\lceil \theta |t| \right\rceil + 1$ first tokens, where $|t|$ is the total number of tokens in a block, and $\theta$ is a Similarity Threshold, i.e. the fraction of the tokens in two blocks that must correspond in order for the blocks to be considered clones. Compared blocks must share at least one token in their prefixes to pass this filtering, in other words, if blocks do not share at least one token in their prefixes, they cannot be clones, and if they do, this block pair requires further comparison. There are many ways to sort the list of tokens in a block, one of the most natural of them is to sort them by frequency.

The sorting of tokens is exploited in the second filtering heuristic, called token position filtering. It is possible to cut down the number of fully processed pairs even further, because the first filter misses a lot of block pairs of different sizes that eventually turn out not to be clones. This algorithm runs another check after comparing prefixes: it adds the number of common tokens in the prefixes and the remaining number of tokens in the smaller of two blocks (without prefix) and compares this number to the necessary number of common tokens to be considered clones $[\theta \cdot \max(|t_1|, |t_2|)]$. If this sum is smaller than the necessary number of tokens, then it is obvious that these two blocks cannot be clones even if all the remaining tokens are the same, and therefore further comparison is not required. This filtering turns out to be very effective and is largely a reason SourcererCC is so efficient and scalable.

Nishi and Damera-Venkatesh [18] complement the described heuristics with a third one, adaptive prefix filtering. Instead of searching for one matching token in the first $|t| - \left\lceil \theta |t| \right\rceil + 1$ tokens, one also might check for $l$ matching tokens in the first $|t| - \left\lceil \theta |t| \right\rceil + l$, while increasing $l$ for a gradual, token-by-token comparison of the blocks. The core idea of the proposed method lies in optimizing the trade-off between the filtering cost (the cost of a deeper checking of the prefixes of blocks) and the verification cost (the cost of the full comparison of two blocks) to decrease the operating time.

Overall, a number of implemented heuristics and additions to the clone detection processes exist, many of which strive to reduce the operating time of the tool to ensure its scalability.

However, other tasks might require different type of modifications. Keeping the scalability in mind, for the tasks of detecting plagiarism and licensing violations, for example, it is of interest to detect smaller less similar clones to check them manually. In this case, the operation time of the process is not that important if it is still reasonable, because the clone detection only takes place once. We propose a technique for token-based clone detection that allows to detect a larger number of diverse clones of various sizes. The next section describes the proposed approach in detail.

3 METHODOLOGY

Let us firstly explain the principal idea behind our technique and then propose a possible optimization that would make it even more useful in practice.

3.1 Possible clones space and parametric curve

The idea of the proposed modification to token-based clone detection is demonstrated and explained in Figure 1 and Figure 2. Every pair of blocks can be expressed as a pair of two numbers: its length in tokens (the length of the smaller of two blocks) and its similarity (which in this paper is considered as the amount of tokens they share divided by the total amount of tokens in the larger block). These numbers can be used as coordinates, and the pair $A (S_A, L_A)$ in Figure 1 contains blocks that are larger and more similar than those in pair $B (S_B, L_B)$. In that sense, choosing the parameters for running token-based clone detection (Similarity Threshold and Lower Token Length Threshold, described in detail in Section 2.2) means choosing the area of the plane that a researcher considers to represent valid clones they want to detect. Running the tool with parameters $(0, 0+)$ would list all the pairs as clones, because it would consider even the smallest and completely dissimilar pairs to be passable. The plus sign in this case represents the fact that no Upper bound is set for the tokens. Graphically, that means detecting the clones over the entire plane.

So, when a researcher chooses the parameters, only the pairs that are larger and more similar than these parameters are considered to be clones. Since, firstly, code clones are somewhat subjective (or, at the very least, arguable) and, secondly, different tasks require
different definitions and restrictions of the term clone, it is very important to choose the parameters carefully. In the example of Figure 1, the pair of parameters \((S_{TH}, L_{TH}+)\) was chosen so that the search yielded the highlighted area. With such parameters, the pairs with parameters equivalent to pair A would be detected as clones, while the pairs with parameters equivalent to pair B would not, because they would not be considered large enough and similar enough. In the resulting area, a researcher might pick a certain sample of the detected pairs to determine the precision of the technique by manually labeling the results as clones or false positive non-clones.

Various studies suggest different parameters that they consider to be the best.

- To detect the most similar files and pieces of code, Lopes et al. [16], Ragkhitwetsagul et al. [19], and Yang et al. [30] use 80% Similarity Threshold.
- Sajnani et al. [23] and Saini and Sajnani [22] set Similarity Threshold values of 70% and also implement a Lower Token Length Threshold to ignore empty or trivial methods.
- In a comparative analysis of precision of various clone detection tools, Farmahinifarahani et al. [9] also use a 70% Similarity Threshold, but no Lower Token Length Threshold.

However, for any exact definition of a clone, one might make a reasonable assumption that clones are neither spread evenly on the possible clones plane, nor do they have any straight borders that would allow us to detect them with a single perfect run. For example, naturally, the more similar right side of the plane is more likely to constitute valid clones. Instead, if one was to present various areas of detection with the same precision in this plane (i.e. the areas that have the same ratio of valid clones to detected pairs), it might look like Figure 2: the larger the blocks in a pair, the lesser similarity threshold they require to be a valid clone because of sub-block similarities (same lines of code that make up only a part of a large block). In other words, copying large units of code leaves more room for modification so that similarities are still significant enough to be considered clones. That is especially relevant for clone detection between different systems, like in the case of plagiarism detection, because (1) it is better to detect more clones and check them more rigorously and (2) if two large blocks of code have the exact same part (even if their other parts somehow differ), this can still be a violation.

If the assumption that valid clones are spread like that is true, that means that by picking a single pair of parameters (like in Figure 1), researchers lose all the data corresponding to the extra highlighted area in Figure 2 that makes up different groups of clone pairs. And if they were to search for clones using the smallest similarity and the smallest length in tokens, they would also detect smaller pieces of code with similar tokens that might not be valid clones (white area in Figure 2). The precision of each of the added parts can be estimated similar to the way that the precision of a single run is estimated, by picking and labeling a sample of clones or by comparing it to ground truth if possible.

Therefore, it is possible to conduct several instances of clone detection with different parameter configurations aimed at different groups of clones and merge the results together to detect more clones of a more diverse nature, which might be of special interest to the task of detecting code reuse between different projects. We call this set of different parameter configurations a parametric curve, and estimating the points of this parametric curve constitutes carrying out multi-objective optimization for the task of detecting valid clones in the possible clones space. This method produces a large overlap and can therefore be considered as converting temporal or computational resources into the amount of detected pairs without losing precision, which is well suited for large-scale studies that require a single case of clone detecting and value fullness over cost-effectiveness, such as detecting possible violations or studying the developing practices in a large corpus of projects.
3.2 Optimization of the search process

The main disadvantage of the described approach is the significant amount of extra operating time or resources spent on finding the same clone pairs in different runs of clone detection (we refer to them as search instances), which is visualized as an overlap of rectangular areas in Figure 2. If the similarity function is simply the fraction of the shared tokens, this can be optimized.

Ideally, instead of doing such a redundant work, the optimal solution would be to detect clones as presented in Figure 3. Since tools can be configured to search within a certain range of token length, this can seemingly be achieved by setting the Upper Threshold of the instance to be the lower threshold of the next instance. For example, if two adjacent parameter pairs (similarity threshold, token length threshold) on the curve are (75, 40+) and (70, 60+), one could configure the first instance to search for clones in the token range (75, 40–60), relying on the fact that for the same token lengths any results for a more strict search would be included in the results for a less strict search. While that is true, such a straightforward approach would leave certain valid pairs out.

The reason for this is that the search is conducted at Similarity Thresholds less than 100%, meaning that blocks in a pair can be (and in a majority of cases are) of different token length and the coordinates on the plane relate only to the token length of the smallest of two blocks. For example, the above-mentioned example would miss a pair of blocks demonstrated in Figure 4, when one block has 65 tokens, the other one has 55 tokens, and they share 49 of them. The similarity of these blocks is $\frac{49}{\max(55, 60)} = 75.4\%$, meaning that this pair would be considered a clone in the original search with parameters (75, 40+). This clone pair is lost in two search instances with parameters (75, 40–60) and (70, 60+), because the corresponding two blocks are never considered together in the same search instance due to one of them being filtered out by token length in each case: the block with 55 tokens is only recognized in the search with parameters (75, 40–60), and the block with 65 tokens is only recognized in the search with parameters (70, 60+). The presence of any fixed border in token length between two instances would result in a possibility of such losses around the border.

Nonetheless, it is possible to optimize the search by implementing Upper Token Length Threshold calculated to catch all of such cases, meaning that there still will be an overlap in search results but it will be significantly smaller.

To calculate the Upper Token Length Threshold for each search instance, one needs to account for the most extreme possible difference in blocks length. Let us once again consider the example parameter pairs (75, 40+), (70, 60+) and calculate the upper bound for the first one. The largest block that the second instance will not process is 59 blocks. The largest block that can form a valid clone pair with such a block would have to include all of its tokens and have as many different tokens as the Similarity Threshold would allow (see Figure 5). That means that the Upper Token Length Threshold is equal to $\lfloor \frac{59}{0.75} \rfloor = 78$. At Similarity Threshold of 75%, any block larger than that can not have valid clone pairs smaller than 59 tokens, meaning that a pair of blocks of sizes 59 and 79 does not need to be detected because it can never be clones with our parameters. As for a pair of blocks of sizes 60 and 79, it does not...
need to be detected because if it is a valid clone, it will be detected in the instance with parameters (70, 60+).

Therefore, in order not to miss any pairs and at the same time not to do any unnecessary work, one must run this search with parameters (75, 40–78) and (70, 60+), which will account for the most extreme difference in blocks’ size. Naturally, the Upper Token Length Threshold of the second instance can be calculated the same way, taking into account the next search instance, and so on.

In general, the Upper Token Length Threshold for the \( i \)-th instance is calculated as:

\[
UTLT_i = \left[ \frac{LTLT_{i+1} - 1}{ST_i} \right]
\]

(1)

where \( LTLT_{i+1} \) is the Lower Token Length Threshold of the next (less similar) search instance (the run of clone detection with the parameters configuration adjacent to this one on the parametric curve) and \( ST_i \) is the \( i \)-th Similarity Threshold. This is later illustrated in Tables 1 and 2 that is explained in Section 4.

This calculation is carried out from the most similar search instance (i.e. the search instance with the largest Similarity Threshold) downwards. For the least similar search instance, there is no next one, so it has no Upper Token Length Threshold and therefore cannot be optimized in this fashion. If the dataset is too large and the least similar search instance takes significantly longer than the others, one might determine their own absolute Upper Token Length Threshold of the search, considering the fact that units of code of thousands lines of code can also be redundant and present no interest.

Overall, the proposed method consists of conducting clone detection several times with different parameters configurations, implementing the parametric curve and merging the results together to detect a larger amount of different clone pairs. This method can also be optimized via reducing the overlap in the detected clones by calculating the most extreme possible clone pairs and filtering out results that are guaranteed to be detected in the other instances of clone detection.

4 ESTIMATING THE PARAMETERS

We tested and evaluated our method on two prominent token-based clone detection tools. The first one is SourcererCC [23]. SourcererCC is known as one of the most popular lexical clone detectors for its detection of Type-3 clones, good scalability, and fast speed, achieved with the use of filtering heuristics described in Section 2.2.

The second tool that we employ is CloneWorks [28], which was also developed with scalability in mind and was designed to support large-scale analysis. The survey [1] lists CloneWorks as a metrics-based tool, however, it can represent the code as a sequence of tokens, meaning that the measures of Token Length Threshold and Similarity Threshold are applicable and are used in configuration. The special feature of CloneWorks is its rich possibilities for the control over both the tokenization and the clone detection, as well as its high operating speed. The tool can target Types 1, 2, and 3 of clones separately and supports various granularities of tokenization.

Both of these tools support several languages of input code. In our study, we have chosen Java.

4.1 The experiment

The parameter pairs of the discussed parametric curve are inherently unknown and must be determined experimentally. In this section, we describe the dataset that was used for estimating the desired configurations and the experiment that we conducted to obtain them.

The dataset consisted of three prominent Java projects: Spring Framework\(^1\), Guava\(^2\), and OpenJDK\(^3\). These projects have more than a thousand of stars on GitHub and were chosen for their maturity. They also belong to different domains, which helps to avoid bias in the obtained parameter pairs.

The dataset was tokenized (see Section 4.2 for details) with a block level of granularity, and we chose the Lower Token Length Threshold to be at least 19 tokens. This value was estimated experimentally and it corresponds well to the threshold of 6 lines of code that the developers of SourcererCC used in their research [23]. The reason for the threshold is that anything below this value usually amounts to very basic pieces of code performing various universal tasks and produces too many false positives. The examples of such redundant blocks are \texttt{equals(object)}, \texttt{toString()}, and some primitive hashing functions.

With that threshold, we carried out 30 runs of clone detection with Similarity Threshold values in the range from 50% to 80%. That range was chosen because it contains a majority of values that previous researchers considered to be optimal. After that, the first and the second authors labeled the pairs as either true positive or false positive (from the standpoint of performing a similar task using a similar technique) starting from the largest Similarity Threshold and the largest Token Length as follows.

For the largest Similarity Threshold (80%), the authors labeled the largest pairs of clones, and then repeated the process while gradually decreasing the Token Length of the blocks in the pair. The process was stopped when the precision fell down to the desired value of 90%, the current Token Length of the last pair was established as a Lower Token Length Threshold for this Similarity Threshold.

The previous step was repeated for the next, lower Similarity Threshold, excluding all the previously found pairs. Since the run on any given Similarity Threshold includes all the results from the more similar runs with the same Token Length Thresholds, we were only interested in the newly found pairs. That means that the precision for a given instance is not calculated for all the found pairs, but only for those that were not already detected in the previous (more similar) runs.

The reason for this is that the goal in the end is to merge all the results together, meaning taking the results of the search with the highest similarity, then adding the pairs from the next, smaller similarity, that are not yet accounted for, etc. Merging two intersecting sets with a given precision does not guarantee the resulting set to have the same precision, because true positives can be repeated and false positives can accumulate, which is why we measure the precision of only the added part.

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\(^1\)Spring Framework: https://github.com/spring-projects/spring-framework

\(^2\)Guava: https://github.com/google/guava

\(^3\)OpenJDK: https://github.com/openjdk/jdk
we have noticed that our hypothesis stated in Section 3.1 is true:

Table 1: Parametric curve configurations for SourcererCC for 90% precision. ST is Similarity Threshold, LTLT and UTLT are Lower and Upper Token Length thresholds, respectively.

| ST  | 75 | 73 | 71 | 70 | 65 | 60 | 55 | 50 |
|-----|----|----|----|----|----|----|----|----|
| LTLT| 19 | 24 | 34 | 36 | 56 | 65 | 144| 215|
| UTLT| 30 | 45 | 49 | 78 | 98 | 238| 389| ∞  |

Table 2: Parametric curve configurations for CloneWorks for 90% precision. ST is Similarity Threshold, LTLT and UTLT are Lower and Upper Token Length thresholds, respectively.

| ST  | 77 | 75 | 72 | 71 | 70 | 65 | 60 | 55 |
|-----|----|----|----|----|----|----|----|----|
| LTLT| 19 | 22 | 24 | 30 | 35 | 50 | 72 | 140|
| UTLT| 27 | 30 | 40 | 47 | 70 | 109| 231| ∞  |

Once we conducted this process for every studied value of the Similarity Threshold, we drew up the results in a single table. If two adjacent Similarity Thresholds corresponded to the same value of Lower Token Length Threshold, only the smaller value of Similarity Threshold was kept, because, as previously mentioned, it contained all the results from the higher values (see clone detection space in Figures 1 and 2).

As a final step, we calculated the Upper Token Length Threshold using Equation 1.

4.2 Parameter pairs

For SourcererCC, tokenization was performed in blocks mode, the resulting list consisted of 8 parameter pairs and is presented in Table 1. For CloneWorks, the tokenization was performed for functions, the type of tokenization was chosen to be \texttt{type3token} as the most similar one to SourcererCC, however, different implementations of tokenization in tools can lead to different results of clone detection. The resulting parameters are presented in Table 2. The resulting parameter pairs strongly correlate to the ones of SourcererCC, indicating that different token-based clone detectors behave similarly in this regard.

During the evaluation of parameter pairs for both clone detectors, we have noticed that our hypothesis stated in Section 3.1 is true: the larger the blocks, the lesser similarity they require to still be considered clones. The reason for this is the following. At high similarity thresholds (75–80%) almost all detected pieces of code are valid clones, but for the lower similarities the situation is different for small and large pieces of code. For the smaller ones, due to their simpler structure, only 55–65% of coinciding tokens sometimes indicate a shuffle of similar identifiers and keywords, which leads to the presence of more false positives in this area of the possible clones space (white area under the curve in Figure 2). However, the same similarity thresholds for the larger blocks very often indicate the presence of the same structures with some insertions, albeit large ones. Since larger blocks have more room for these insertions, the resulting pairs can often be still considered clones in some application of clone detection. For example, if we are looking for plagiarism and consider two similar blocks of 20 lines to be viable candidates, we would still be interested in two blocks of 40 lines where 20 or 30 lines are the same.

One must note that the ideas of similar and dissimilar pieces of code, as well as them being small and large are conditional and therefore need to be determined specifically for different definitions of clones.

5 EVALUATION

5.1 Datasets

To evaluate the increase in the amount of detected clone pairs with the proposed method, as well as to capture the effects of the possible optimization, we performed an evaluation on two datasets of different sizes to better capture the efficiency of the possible scaling.

For the first test, we chose three other prominent Java repositories: Mockito\(^4\), Java Design Patterns\(^5\), and RxJava\(^6\) because of their popularity and their relatively small size. SourcererCC tokenization reveals just 41,145 unique blocks of code in this dataset.

Such a small dataset presents one of the possible use cases for clone detection, however, it is not universal. To test the scalability of the optimization and also to run it in a completely different setting, we have used a second dataset an order of magnitude larger than the previous one, which consisted of a single large project IntelliJ IDEA\(^7\). SourcererCC tokenization parsed this repository into 394,574 blocks of code. Not only would the operation time be different here, clones in a single large system can have entirely different structure.

The search was carried out on an Amazon Web Services (AWS) server with Intel Xeon Platinum 8175M @ 2.50 GHz and 30 GB of RAM.

5.2 SourcererCC

The results of the search in the smaller dataset with SourcererCC are presented in Table 3. The best results from a single parameter pair were obtained for a Similarity Threshold of 75% in 02 min 58 s (including tokenization), 35,020 unique pairs were found altogether. After merging the results of 8 search instances from the parametric curve, 49,709 unique pairs were detected in 18 min 38 s, which correlates to an increase in the amount of detected pairs of 41.9% in six times the operation time.

Table 3 also shows that after the implementation of the optimization, the total number of detected unique pairs (after merging) stayed the same, meaning that the use of Upper Token Length Thresholds indeed did not lose any clones, and the number of detected overlapping pairs (simply a sum of all the detected pairs in different instances, indicating the degree of overlap between these instances) went down from 138,489 to 82,827. However, the operating time barely changed. The reason for that and the fact that all the instances of clone detection have virtually the same operating time is that the clone detection itself (the comparison of the

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\(^4\)Mockito: https://github.com/mockito/mockito

\(^5\)Java Design Patterns: https://github.com/iluwatar/java-design-patterns/

\(^6\)RxJava: https://github.com/ReactiveX/RxJava/

\(^7\)IntelliJ IDEA: https://github.com/JetBrains/intellij-community/
blocks) is almost immediate for such a small number of blocks, the operating time mostly consists of various preprocessing for more rapid clone detection. That means that in this case the optimization cannot manifest itself.

The situation is different for the second dataset, consisting of a single large repository. The results of the test are presented in Table 4. Once again, the best result for a single search instance was obtained for Similarity Threshold 75% in 12 min 42 s (including tokenization), 139,075 unique pairs were detected altogether. Implementing the parametric curve allowed to detect 202,927 unique clones in 39 min 14 s, correlating to an increase of 45.9% in three times the time, so, more efficiently than a smaller dataset.

The optimization decreased the amount of overlapping detected pairs from 570,504 to 411,400, but with a larger dataset this also decreased the operating time from 39 min 14 s to 31 min 22 s (a decrease of 20.1%), making it only 2.5 times slower than a run on a single parameter pair. It can be expected that for larger datasets, this optimization can bring even more significant results. It can be noted that in this specific case when the tokenization takes more time than clone detection, the technique is even more useful due to the fact that tokenization is performed one time in both cases.

### 5.3 CloneWorks

The results for the smaller dataset using CloneWorks are presented in Table 5. The most amount of clone pairs were detected for the

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Table 3: Results of clone detection with the parametric curve with SourcererCC on a smaller dataset. ST is Similarity Threshold.

| Stage     | No optimization | Optimization |
|-----------|-----------------|--------------|
|           | Time, s         | Pairs        | Time, s         | Pairs        |
| Tokenization |                |              |                |              |
| ST 75     | 136             | 133          | 35,020         | 13,842       |
| ST 73     | 140             | 134          | 31,893         | 17,971       |
| ST 71     | 135             | 134          | 23,309         | 9,783        |
| ST 70     | 134             | 134          | 23,346         | 19,358       |
| ST 65     | 133             | 133          | 10,835         | 10,791       |
| ST 60     | 132             | 132          | 10,138         | 10,264       |
| ST 55     | 132             | 132          | 84             | 84           |
| Merging   | < 1             | < 1          |                |              |
| Total     | 1,118           | 1,106        | 138,489        | 82,827       |

Unique: 49,709

Table 4: Results of clone detection with the parametric curve with SourcererCC on a larger dataset. ST is Similarity Threshold.

| Stage     | No optimization | Optimization |
|-----------|-----------------|--------------|
|           | Time, s         | Pairs        | Time, s         | Pairs        |
| Tokenization |                |              |                |              |
| ST 77     | 2.4             | 1.2          | 30,569         | 9,197        |
| ST 75     | 2.7             | 1.3          | 26,539         | 8,483        |
| ST 72     | 2.9             | 1.6          | 22,280         | 13,387       |
| ST 71     | 2.5             | 1.6          | 16,911         | 18,983       |
| ST 65     | 2.5             | 1.9          | 4,114          | 3,198        |
| ST 60     | 1.9             | 1.5          | 2,133          | 1,965        |
| ST 55     | 1.3             | 1.3          | 626            | 626          |
| Merging   | 0.2             | 0.2          |                |              |
| Total     | 273.2           | 269.2        | 135,429        | 87,243       |

Unique: 52,881

Table 5: Results of clone detection with the parametric curve with CloneWorks on a smaller dataset. ST is Similarity Threshold.

| Stage     | No optimization | Optimization |
|-----------|-----------------|--------------|
|           | Time, s         | Pairs        | Time, s         | Pairs        |
| Tokenization |                |              |                |              |
| ST 77     | 18              | 18           |                |              |
| ST 75     | 2.4             | 1.2          | 30,569         | 9,197        |
| ST 72     | 2.7             | 1.3          | 26,539         | 8,483        |
| ST 71     | 2.9             | 1.6          | 22,280         | 13,387       |
| ST 65     | 2.5             | 1.9          | 4,114          | 3,198        |
| ST 60     | 1.9             | 1.5          | 2,133          | 1,965        |
| ST 55     | 1.3             | 1.3          | 626            | 626          |
| Merging   | 0.2             | 0.2          |                |              |
| Total     | 37              | 30.6         | 175,781        | 90,590       |

Unique: 52,881

Table 6: Results of clone detection with the parametric curve with CloneWorks on a larger dataset. ST is Similarity Threshold.

| Stage     | No optimization | Optimization |
|-----------|-----------------|--------------|
|           | Time, s         | Pairs        | Time, s         | Pairs        |
| Tokenization |                |              |                |              |
| ST 77     | 5.9             | 4.4          | 33,837         | 18,760       |
| ST 75     | 5.6             | 4.3          | 26,539         | 9,562        |
| ST 72     | 5.7             | 4.8          | 28,989         | 18,615       |
| ST 71     | 5.3             | 4.8          | 22,280         | 18,983       |
| ST 65     | 5.3             | 5            | 16,911         | 15,534       |
| ST 60     | 4.8             | 5.1          | 4,114          | 3,198        |
| ST 55     | 4.7             | 4.9          | 2,133          | 1,965        |
| ST 60     | 3.7             | 3.7          | 626            | 626          |
| Merging   | 0.2             | 0.2          |                |              |
| Total     | 273.2           | 269.2        | 135,429        | 87,243       |

Unique: 48,572
The overall results of the evaluation are presented in Table 7. Even a specific intent of a possible legal action, it is preferable to spend fragments. Moreover, when conducting plagiarism analysis with a tool that often deals with various small modifications to the code and maintenance. As for the inter-project clones, this method can somewhat less similar code fragments might indicate a need of in a variety of different cases.

Table 7: The overall results of the evaluation.

| Clone detection tool | Dataset   | Increase in the amount of detected clones | Increase of the operating time without optimization | Increase of the operating time with optimization |
|----------------------|-----------|------------------------------------------|---------------------------------------------------|-----------------------------------------------|
| SourcererCC          | Smaller   | 41.9%                                    | 528%                                              | 521%                                          |
|                      | Larger    | 45.9%                                    | 209%                                              | 147%                                          |
| CloneWorks           | Smaller   | 52.7%                                    | 77%                                               | 46%                                           |
|                      | Larger    | 44.1%                                    | 15%                                               | 13%                                           |

Similarity Threshold of 72%, a total of 34,642 unique clones in 20.9 seconds. After the merging of the results from the entire parametric curve, the total amount of detected unique clone pairs was equal to 52,881, detected in 37 seconds, correlating to an increase in the amount of found pairs of 52.7% and an increase in operating time of only 77%. It can be noted here that for CloneWorks, the proposed method is even more useful because of its rapid clone detection stage.

Table 5 also shows that after the implementation of the optimization, the total amount of detected overlapping clones decreased from 175,781 to 90,590, and the operating time of the tool was brought down from 37 seconds to 30.6 seconds (a decrease of 17.3%), making it only 46% slower than the original run.

Table 6 shows the results of the tool’s performance on the second, larger dataset. The best results for an individual instance of clone detection are 33,837 unique pairs for a Similarity Threshold of 77%, obtained in 3 min 58 s. Merged results from the entire curve amount to 48,752 unique pairs detected in 4 min 33 s, increasing the output by 44.1% and increasing the time by only 15%.

The implementation of the optimization decreased the amount of detected overlapped pairs from 135,429 to 87,243, and the operating time of the tool was brought down from 37 seconds to 30.6 seconds (a decrease of 17.3%), making it only 46% slower than the original run.

The implementation of the optimization decreased the amount of detected overlapped pairs from 135,429 to 87,243, and the operating time of the tool was brought down from 37 seconds to 30.6 seconds (a decrease of 17.3%), making it only 46% slower than the original run.

The operating time of clone detection with this method can also be managed. As can be seen in Table 7, situations differ. If in a specific clone detection task with a specific tool tokenization takes more time than clone detection, then the implementation of the parametric curve search will not increase the operating time that drastically. On the other hand, if clone detection itself takes more time than the tokenization, it can be expedited by using the described optimization.

The main feature of the proposed approach is its adjustability. The method can be applied to any token-based clone detector, and the Lower and Upper absolute Token Length Threshold can be implemented to fit the researcher’s definition of trivial and unreasonable pieces of code, making it useful for a lot of different applications.

6 THREATS TO VALIDITY

This work deals with several threats to validity:

Fundamentally, when it comes to clone detection, a lot of concepts in this process are rather subjective. In this research, we have implemented a universal Token Length threshold and excluded trivial pieces of code based on our own preliminary experiments. In general, the exact definition of a code clone depends on the task and on the eye of the beholder, and in our work we have considered clones as they are understood in the large-scale search between repositories, since it is the main use case of the proposed approach.

From a technical standpoint, it is desirable to conduct a more thorough expert labeling of the obtained configurations. We cannot be completely sure that our labeling of parameter pairs is general for any possible cases, however, two studied tools provided similar values which might mitigate the risk.

Also, in our research we have limited our scope to Java as the language, SourcererCC and CloneWorks as clone detection tools, and used a set of specific projects for estimating the parameters and for the evaluation. Code clones in different languages might behave slightly different from the standpoint of specific parameters that we study, so we plan on studying them in future work.

Overall, even though these threats are worth noting, we believe that they do not invalidate the results, because the implementation of the parametric curve allows us to detect more diverse code clones and because discussing code clones in terms of points on the possible clones space with search parameters as axes can be
used in further research to better understand the nature of clone detection.

7 CONCLUSION AND FUTURE WORK

In this paper, we proposed and evaluated a modification to token-based clone detection that consists in conducting the search several times with different parameters aimed at different groups of clones and merging the results together. We also discussed the possible optimization to this approach that accounts for the most extreme possible clone pairs to calculate the Upper Token Length Threshold of each clone detection run.

We have estimated the necessary parameter pairs for two prominent token-based clone detection tools, SourcererCC and CloneWorks, and have discovered that these parameter pairs strongly correlate to each other. Implementation of the parametric curve for SourcererCC allowed us to increase the amount of detected clone pairs for the tool without lowering its precision. Running the tool with 8 different parameter pairs allowed us to obtain 41.9% more results for one of the datasets and 45.9% for another. This technique requires significantly more time or computational resources, but is well-suited for studies that require a single instance of clone detection, such as detection of reuse of code or a large-scale research of developers’ software practices. We also showed that the proposed method can be optimized: for a larger dataset we were able to decrease the operating time by 20.0% by minimizing the overlap of the search instances as narrowly as possible.

Experiments with CloneWorks also demonstrated a significant increase in the amount of detected clones (52.7% and 44.1%). They also showed that for some cases, when tokenization of the code takes long enough, the implementation of the proposed approach does not increase the operating time as significantly as for others, and therefore the optimization itself is not really necessary.

Overall, the proposed technique is rather flexible and can be applied to various cases of clone detection.

Several possible directions for future work are possible:

- It is of interest to repeat this study for other prominent programming languages (Python, JavaScript, C++) and re-search the similarities and differences between such cases. It is possible that other languages behave differently from the standpoint of specific parameters that we incorporate in our work.

- There is a possibility to look for the ways to modify the parametric curve to exclude obsolete pieces of code even more efficiently. For instance, in this paper, we only considered small trivial pieces of code, perhaps, it is possible to identify a certain absolute Upper Token Length threshold to exclude redundant large pieces of code.

- The concept presented in this paper deals with the size of the piece of code in terms of tokens, however, it can be expressed with different types of code representations. It can be implemented in the textual approaches, and even more interestingly, it might be applicable to tree-based clone detection tools if one was to filter the pieces of code by the size of the sub-tree.

Clone detection plays a key role in different areas of software engineering: plagiarism detection, optimizing code maintenance, and many others. Perfecting the tools and creating new techniques for clone detection may help us get a better understanding of coding practices throughout the industry and assist in conducting various research.

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