# SCDetector: Software Functional Clone Detection Based on Semantic Tokens Analysis


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## Abstract

Code clone detection is to find out code fragments with similar functionalities, which has been more and more important in software engineering. Many approaches have been proposed to detect code clones, in which token-based methods are the most scalable but cannot handle semantic clones because of the lack of consideration of program semantics. To address the issue, researchers conduct program analysis to distill the program semantics into a graph representation and detect clones by matching the graphs. However, such approaches suffer from low scalability since graph matching is typically time-consuming.

In this paper, we propose *SCDetector* to combine the scalability of token-based methods with the accuracy of graph-based methods for software functional clone detection. Given a function source code, we first extract the control flow graph by static analysis. Instead of using traditional heavyweight graph matching, we treat the graph as a social network and apply social-network-centrality analysis to dig out the centrality of each basic block. Then we assign the centrality to each token in a basic block and sum the centrality of the same token in different basic blocks. By this, a graph is turned into certain tokens with graph details (*i.e.,* centrality), called semantic tokens. Finally, these semantic tokens are fed into a Siamese architecture neural network to train a code clone detector. We evaluate *SCDetector* on two large datasets of functionally similar code. Experimental results indicate that our system is superior to four state-of-the-art methods (*i.e., SourcererCC*, *Deckard*, *RtvNN*, and *ASTNN*) and the time cost of *SCDetector* is 14 times less than a traditional graph-based method (*i.e., CCSharp*) on detecting semantic clones.



## CCS Concepts

• **Software and its engineering → Software maintenance tools**.

## Keywords

Social Network Centrality, Semantic Tokens, Siamese Network

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## 1 INTRODUCTION

Code clone detection aims to dig out code snippets with similar functionalities, which has attracted wide attention in software engineering. Commonly, code clone types are classified into four categories based on the syntactic or semantic level's differences. The first three types of clones are syntactically similar clones, while the last type of clones characterizes semantically similar clones. As for syntactic similarity, it usually occurs when programmers conduct code copying and pasting while semantic similarity is introduced when developers implement certain functionally similar codes from scratch.

Many approaches have been proposed to detect code clones. For example, *CCFinder* [28] extracts a token sequence from the input code by lexical analysis and applies several rule-based transformations to convert the token sequence into a regular form to detect Type-1 and Type-2 clones. In an effort to detect more types of clones, another state-of-the-art token-based tool, *SourcererCC* [43], has been designed. It captures the tokens' overlap similarity among different methods to detect near-miss Type-3 clones. *SourcererCC* [43] is the most scalable code clone detector which can scale to very big code (*e.g.,* 250M line codes). However, because of the lack of consideration of program semantics, these token-based approaches can not handle Type-4 clones (*i.e.,* semantic clones). To address the issues, researchers conduct program analysis to distill the semantics of code fragments into graph representations and perform graph matching (*e.g.,* excavating isomorphic sub-graphs) to measure the similarity between given codes. Compared to token-based techniques [20, 28, 43], these graph-based detectors [32, 34, 50] achieve higher effectiveness on detecting functional code clones. However, they can not scale to big code due to the complexity of graph isomorphism and heavy-weight time consumption of graph matching. Given large-scale clone detection is essential for daily software engineering activities such as code search [30], mining library candidates [22], and license violation detection [19, 33], there is an increasing need for a scalable technique to detect semantic clones on a daily basis.

In this paper, we propose a novel method to combine the scalability of token-based techniques with the accuracy of graph-based approaches to detect semantic code clones. Specifically, we address two major challenges.

- *Challenge 1: How to transform the high-cost graph matching into succinct token analysis while preserving the graph details?*
- *Challenge 2: How to design a scalable yet accurate similarity computation process to handle semantic clones?*

To address the first challenge, we treat the *control flow graph* (CFG) of a method as a social network and apply social-network-centrality analysis to dig out the centrality of all basic blocks of the CFG. Centrality analysis was first introduced in social network analysis while the purpose is to find out the importance of nodes in a network. Centrality can retain the graph details and have the potential to reflect the structural properties of a graph. Therefore, instead of using traditional high-cost graph analysis, we assign the centrality to each token in a basic block and sum the centrality of the same token in different basic blocks. The outputs of this phase are certain tokens with graph details (*i.e.,* centrality), called semantic tokens. By this, we transform the CFG into certain semantic tokens to avoid the high-cost graph matching.

To solve the second challenge, we design a Siamese network [10] to measure the similarity of a code pair. Siamese network has been widely applied in many areas, such as paraphrase scoring, where the inputs are two sentences and the output is a score of how similar they are. Given two methods, the Siamese network first maps them to the same feature space. If they are not a clone pair, the distance between them will be adjusted larger and larger as the training progresses. On the contrary, if the pair is a clone pair, the distance will be adjusted to become smaller with training, making it possible to detect semantic clones although they are syntactically dissimilar.

We implement a prototype system, *SCDetector*, and evaluate it on two widely used datasets, namely Google Code Jam [1] and BigCloneBench [2, 45]. In our experiments, the number of used code pairs are about 1.4 million and 0.28 million in Google Code Jam dataset and BigCloneBench dataset, respectively. Our evaluation results show that *SCDetector* is superior to four state-of-the-art comparative systems including one token-based method (*i.e., SourcererCC* [43]), one tree-based approach (*i.e., Deckard* [24]), and two deep learning-based detectors (*i.e., RtvNN* [53] and *ASTNN* [57]). For example, when detecting clones in BigCloneBench, the F1 scores of *SourcererCC* [43], *Deckard* [24], *RtvNN* [53], and *ASTNN* [57] are 14%, 12%, 1%, and 92% while *SCDetector* is able to maintain 98% of F1. Moreover, we also examine the scalability of *SCDetector* and our comparative systems, the results report that *SCDetector* consumes more time to detect code clones compared to a token-based method (*i.e., SourcererCC* [43]) because of the consideration of graph details. However, compared to a traditional graph-based method (*i.e., CCSharp* [50]), *SCDetector* is 14 times faster on detecting semantic clones.

In summary, this paper makes the following contributions:

- We propose a novel method to transform a CFG into certain semantic tokens (*i.e.,* tokens with graph details) by centrality analysis. The generation of semantic tokens avoids high-cost graph analysis while preserving program semantics on detecting semantic clones.
- We design a prototype system, *SCDetector*[1], to combine the scalability of token-based approaches with the accuracy of graph-based tools for semantic clone detection.
- We conduct comparative evaluations on two widely used datasets, namely Google Code Jam [1] and BigCloneBench [2]. Experimental results show that *SCDetector* is able to maintain the best performance than other four state-of-the-art clone detectors (*i.e., SourcererCC* [43], *Deckard* [24], *RtvNN* [53], and *ASTNN* [57]).

**Paper organization.** The remainder of the paper is organized as follows. Section 2 presents our motivation. Section 3 shows the definitions. Section 4 introduces our system. Section 5 reports the experimental results. Section 6 discusses the future work. Section 7 shows the limitations. Section 8 describes the related work. Section 9 concludes the present paper.

## 2 MOTIVATION

To illustrate how we develop the proposed approach, we use a simplified example, which is a clone pair in BigCloneBench [2]. As shown in List 1 and 2, these two methods[2] are both to calculate the greatest common divisor of two integers. In BigCloneBench, the clone pair is classified into a Type-4 clone, called semantic clone since they implement the same functionality with syntactically dissimilar code.

[1] https://github.com/SCDetector/SCDetector.

[2] The function ID of $gcd_1$.java and $gcd_2$.java in BigCloneBench are 28,840 and 428,867, respectively.

We first illustrate how *SourcererCC* [43] (*i.e.,* a state-of-the-art token-based clone detector) computes the similarity of two methods. *SourcererCC* [43] uses *Overlap* to measure the similarity because it intuitively captures the notion of overlap among different methods. For instance, given two methods $M_1$ and $M_2$, the overlap similarity $S(M_1, M_2)$ is calculated as the ratio between the number of same tokens shared by $M_1$ and $M_2$ and the maximum number of tokens in $M_1$ and $M_2$.

$$S(M_1, M_2) = \frac{|M_1 \bigcap M_2|}{max(|M_1|, |M_2|)}$$

We conduct lexical analysis to parse the methods into several tokens. The analysis results show that the number of tokens in $gcd_1$*.java* and $gcd_2$*.java* is 38 and 32, respectively. Then the same tokens shared by $gcd_1$*.java* and $gcd_2$*.java* are obtained for computing the overlap similarity. We observe that there are 19 same tokens shared by these two methods, in other words, the overlap similarity of $gcd_1$*.java* and $gcd_2$*.java* is 19/38=0.5. The default setting of similarity threshold in *SourcererCC* is 70%, which means that *SourcererCC* reports two methods as a clone pair only when the similarity of them is larger than 70%. In this case *SourcererCC* will cause a false negative by not reporting methods in $gcd_1$*.java* and $gcd_2$*.java* as a clone pair.

```
private long gcd(long a, long b) {
    while (b != 0) {
        long t = a % b;
        a = b;
        b = t;
    }
    return a;
}
```

**List 1: $gcd_1$.java**

```
public static int GCD(int a, int b) {
    if (b == 0) return a;
    return GCD(b, a % b);
}
```

**List 2: $gcd_2$.java**

To achieve a more accurate clone detection, we need to incorporate information on CFGs to reflect program semantics. To achieve a scalable clone detection, we plan to distill the topology of CFGs and program semantics into certain tokens with their corresponding degree. First, we use *Soot* [3] to conduct static analysis to obtain the CFGs of $gcd_1$*.java* and $gcd_2$*.java* where each node is a basic block. Figure 1 presents the two CFGs, it is obvious that although these two methods are syntactically different, their CFGs are structurally similar because they are all designed to achieve the same functionality. Second, we dig out the degree of each basic block and assign the degree value to each token in a basic block. Finally, we sum the degree of the same token in all basic blocks and treat it as the weight of the token. For example, the degree[3] of basic blocks '*a = b*' and '*b = t*' in $gcd_1$*.java* are both 2. Then the weight of tokens *a*, *=*, *b*, *t* are computed as 2, 2+2=4, 2+2=4, and 2, respectively. After obtaining the corresponding weight of all tokens, we compute the overlap similarity by weight instead of by the number of same tokens shared between two methods. In this way, the total weight of all tokens in CFGs of $gcd_1$*.java* and $gcd_2$*.java* are 112 and 79, respectively. After overlap analysis,

[3]The degree consists of in-degree and out-degree.

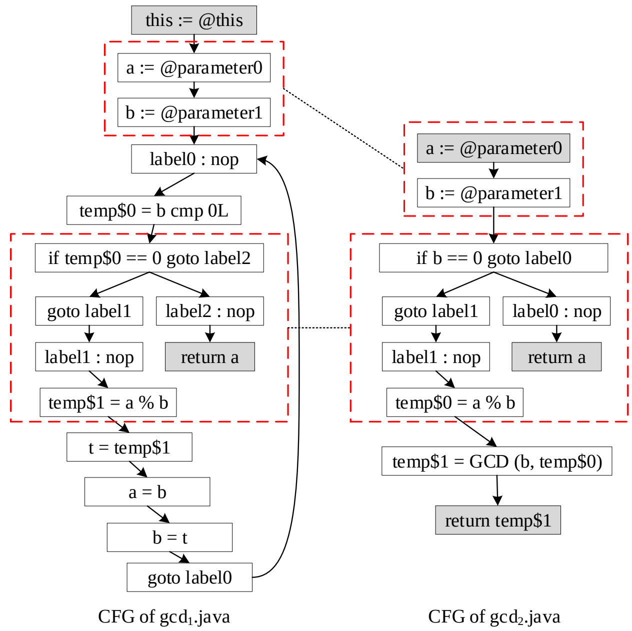


**Figure 1: Control flow graphs of $gcd_1$*.java* and $gcd_2$*.java***

we find that the weight of the same tokens shared by these two graphs is 70. Therefore, the overlap similarity can be calculated as 70/112=0.625 which is greater than 19/38=0.5.

However, clone detection may not be accurate if we only consider the degree of a basic block as the weight in a graph. For example, suppose that there are two CFGs, namely $cfg_1$ and $cfg_2$, the number of basic blocks of these two graphs are 201 and 21, respectively. The degree of two basic blocks ($bb_1$ in $cfg_1$ and $bb_2$ in $cfg_2$) are both 10. It is obvious that the weights of $bb_1$ and $bb_2$ are different because $bb_1$ in $cfg_1$ is associated with half (*i.e.,* 10/20=0.5) of the other basic blocks while $bb_2$ in $cfg_2$ is only associated with 5% (*i.e.,* 10/200=0.05) of other basic blocks.

**Table 1: The similarity of different types of tokens between $gcd_1$*.java* and $gcd_2$*.java***

| Token Type | OriToken_Num | DegreeToken_Num | |
|---|---|---|---|
| | | No Normalization | Normalization |
| $gcd_1$*.java* | 38 | 112 | 8 |
| $gcd_2$*.java* | 32 | 79 | 8.7778 |
| Same_Num | 19 | 70 | 6.3889 |
| Similarity | 0.5 | 0.625 | 0.7986 |

Therefore, we compute another weight of tokens by normalizing the sum of degree. In other words, the weight of a token is normalized by dividing by the maximum possible degree in a graph *N-1* where *N* is the number of nodes in the graph. As shown in Figure 1, the number of basic blocks in $gcd_1$*.java* and $gcd_2$*.java* are 15 and 10, respectively. Therefore, the normalized weight of all tokens in these two graphs can be computed as 112/(15-1)=8 and 79/(10-1)=8.7778, respectively. Similarly, we discover that the normalized weight of the same tokens shared by these two graphs is 6.3889. In other words, the overlap similarity will be 6.3889/8.7778=0.7986 which is the highest among the three calculated similarities presented in Table 1.

In conclusion, $gcd_1$*.java* and $gcd_2$*.java* will not be detected as a clone pair if we only consider the frequency or total degree as the weight of each token. However, when we use the normalized degree as the graph details to conduct similarity computation, the code pair can be detected as a clone pair. In other words, transforming a graph representation into tokens with normalized degrees may be a great candidate for handling semantic clones.

Therefore, based on the observation, we propose a novel method by transforming the graph details into tokens with normalized degrees for semantic clone detection.

# 3 DEFINITIONS

Before introducing our proposed system, we first describe the formal definitions that we use throughout the paper.

```
1  //original
2  private long gcd(long a, long b) {
3      while (b != 0) {
4          long t = a % b;
5          a = b;
6          b = t;
7      }
8      return a;
9  }
10
11 //Type-1
12 private long gcd(long a, long b) {
13     while (b != 0) {
14         long t = a % b;
15         a = b;
16         b = t;
17     }
18     return a;
19 }
20
21 //Type-2
22 private long gcd(long m, long n) {
23     while (n != 0) {
24         long t = m % n;
25         m = n;
26         n = t;
27     }
28     return m;
29 }
30
31 //Type-3
32 public static int calculateGCD(int a, int b) {
33     while (b != 0) {
34         int t = a;
35         a = b;
36         b = t % b;
37     }
38     return a;
39 }
40
41 //Type-4
42 public static int GCD(int a, int b) {
43     if (b == 0) return a;
44     return GCD(b, a % b);
45 }
```

**List 3: Examples of different clone types**

## 3.1 Clone Type

In our paper, we use the following well-accepted definitions [11, 41] of code clone types.

- **Type-1 (textual similarity)**: Identical code fragments, except for differences in white-space, layout, and comments.
- **Type-2 (lexical similarity)**: Identical code fragments, except for differences in identifier names and literal values, in addition to Type-1 clone differences.
- **Type-3 (syntactic similarity)**: Syntactically similar code fragments that differ at the statement level. The fragments have statements added, modified and/or removed with respect to each other, in addition to Type-1 and Type-2 clone differences.
- **Type-4 (semantic similarity)**: Syntactically dissimilar code fragments that implement the same functionality.

To elaborate on the different types of clones, List 3 presents an example from Type-1 to Type-4 clones. The original method is to compute the greatest common divisor of two numbers. The Type-1 clone (starting in line 12) is identical to the original method. The Type-2 clone (starting in line 22) differs only in identifiers name (*i.e., m* and *n* instead of *a* and *b*). Obviously, the two types mentioned above are easy to detect. The Type-3 clone (starting in line 32) is syntactically similar but differs at the statement level. The first line in Type-3 (line 32) is totally different from the origin (line 2). The method name and types of parameters are all changed. In addition, it calculates the greatest common divisor in a similar but not identical way. Detecting Type-3 clones is harder than the previous two types. Finally, the Type-4 clone (starting in line 42) iterates to compute the greatest common divisor which is a completely different way. Its lexical and syntactic are dissimilar to the original method. Therefore, it requires an in-depth understanding of code fragments to detect Type-4 clones.

## 3.2 Code Granularity

We also specify a granularity unit which refers to the scale of a code fragment.

- **Token**: This is the minimum unit the compiler can understand. For example, in the statement '*int i = 0;*' five tokens exist: *int*, *i*, *=*, *0*, and *;*.
- **Line**: This represents a sequence of tokens delimited by a new-line character.
- **Function**: This is a collection of consecutive lines that perform a specific task.
- **File**: This contains a set of functions. A file may in fact contain no functions. However, most source files usually contain multiple functions.
- **Program**: This is a collection of files.

In summary, a program is a collection of files containing functions, and a function is a collection of lines that are composed of tokens. Code cloning can occur at any of the listed granularity units. File-level and program-level code clone detection is too coarse while line-level and token-level may detect many meaningless clone pairs (*e.g.,* '*int i = 0;*' and '*int j = 0;*' may be detected as a clone pair). Therefore, we take a function as our processing granularity since it implements a specific functionality.

## 3.3 Centrality

Prior work has validated the effectiveness of centrality analysis on different areas, such as biological network [23], co-authorship network [36], transportation network [21], criminal network [13], and affiliation network [16]. The wide usage of centrality indicates

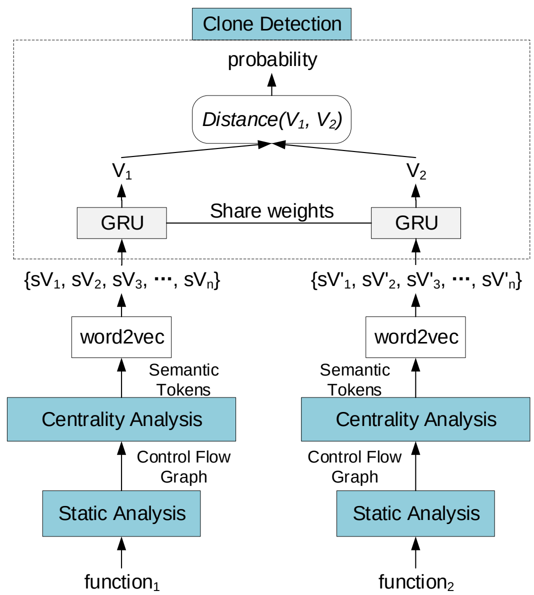


**Figure 2: System architecture of *SCDetector***

that it is very useful and has the ability to retain the network structural properties for network analysis.

Centrality concepts were first developed in social network analysis which quantifies the importance of a node in the network. There has been proposed different centrality measures in a social network, such as *degree centrality* [18], *closeness centrality* [18], *betweenness centrality* [17], and *katz centrality* [29]. Prior work [54] has suggested that degree centrality can achieve the highest efficiency while maintaining high effectiveness on graph analysis among the listed centrality measures. Therefore, in order to conduct more scalable code clone detection, we choose degree centrality to develop our proposed system. The degree centrality [18] of a node is defined as the fraction of nodes it is connected to. The degree centrality values are normalized by dividing by the maximum possible degree in a graph $N$ -1 where $N$ is the number of nodes in the graph. Note that $deg(v)$ is the degree of node $v$.

$$C_D(v) = \frac{deg(v)}{N-1}$$

# 4 SYSTEM ARCHITECTURE

In this section, we introduce our proposed system, namely *SCDetector* (***S**emantic **C**lone **Detector***).

## 4.1 System Overview

As shown in Figure 2, *SCDetector* consists of three main phases: *Static Analysis*, *Centrality Analysis*, and *Clone Detection*.

- ***Static Analysis***: This phase aims to extract the CFG of a method based on static analysis, where each node is a basic block. The input in this phase is a method while the output is the CFG of the method.
- ***Centrality Analysis***: In this phase, we first dig out the centrality of each basic block of the CFG obtained from static analysis. Then we assign the centrality to each token in a basic block and sum the centrality of the same token in different basic blocks. The outputs are tokens with graph details (i.e., centrality), called semantic tokens.
- ***Clone Detection***: Given a pair of code methods, the corresponding semantic tokens are fed into a Siamese network. The output is the probability that these two methods are a clone pair. If the probability is large than 0.5, we identify that they are a pair of clones. The Siamese network is trained first by using labeled code pairs.

## 4.2 Static Analysis

In this paper, we aim to combine the scalability of token-based methods with the accuracy of graph-based methods for semantic clone detection. Therefore, we first conduct static analysis to extract the graph representation of a program. Because the programming language of the experimental dataset is *Java*, we implement our static analysis based on a java optimization framework, namely *Soot* [3], which has been used by many papers [48, 55]. In fact, the purpose of static analysis is to convert a method into a graph representation. It is not limited to which programming language (*e.g., Java* and *C/C++*) the method is since different programming languages have corresponding static analysis tools to analyze them. For example, we leverage *Soot* [3] to obtain the CFG of a *Java* method while others can use *Joern* [4] to extract the CFG of a *C* method.

To better illustrate the different phases involved in our system, we choose the method in List 2 as an example and present a more clear description in Figure 3 about the three main steps.

## 4.3 Centrality Analysis

Instead of using traditional graph matching to measure the graph similarity of two graphs, we treat a CFG as a social network and conduct centrality analysis to excavate the graph details for more efficient similarity computation. Centrality concepts were first developed in social network analysis which quantify the importance of a node in the network and have the potential to unveil the structural patterns of the network. Many different types of centrality measures (*e.g.,* degree centrality and closeness centrality) have been proposed for network analysis in different areas. In this paper, we select degree centrality to commence our centrality analysis since degree centrality is able to achieve the highest scalability while maintaining high effectiveness on graph analysis among many centrality measures [54].

Given a CFG, we first extract the degree centrality of all basic blocks in the graph. A basic block is composed of several tokens, which can be obtained by lexical analysis. For example, basic clock '*if b == 0 goto label0*' consists of six tokens which are *if*, *b*, *==*, *0*, *goto*, and *label0*. After degree centrality analysis, we assign the corresponding centrality to all tokens in a basic block and compute the total centrality of the same token in different basic blocks. To better describe the main steps, we present a detailed example in Figure 3. As shown in Figure 3, the degree centrality of two basic blocks '*return a*' and '*return temp$1*' are both 0.11. Then the total degree centrality of token *return* can be computed as 0.11+0.11=0.22. After centrality analysis, we can obtain the corresponding total

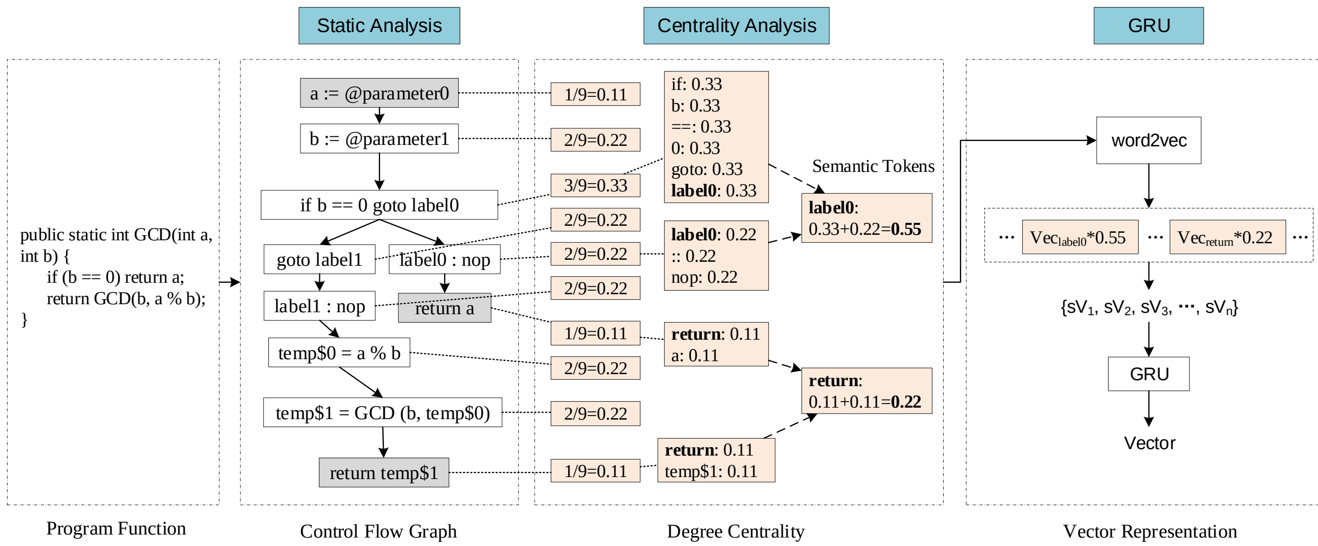


**Figure 3: Program encoder phase of *SCDetector***

degree centrality of all tokens in a CFG. We call these tokens with total degree centrality as semantic tokens.

In brief, the input of centrality analysis is a CFG and the outputs are tokens with graph details (*i.e.,* centrality), called semantic tokens.

## 4.4 Clone Detection

Deep learning generally refers to a series of machine learning algorithms built on a neural network structure that contains multiple layers of nonlinear transformations to abstract and learn the representation of data. These methods provide effective solutions due to their powerful feature learning ability. They have greatly promoted the progress of image processing, language recognition, and other fields, and have also attracted wide attention in the field of natural language processing.

After centrality analysis, the CFG of a method is transformed into certain semantic tokens. As a matter of fact, these tokens are indeed words. If we sort these words according to the first letter, then these words can be regarded as a sentence. Therefore, we can apply techniques in the field of natural language processing to encode the sentence into vector representation for efficiently similarity computation.

*Long Short Term Memory* (LSTM [56]) and *Gated Recurrent Unit* (GRU [8, 47]) are the most widely used deep learning models in natural language processing because of the high effectiveness on text processing. Prior studies [57] have validated that GRU can achieve almost the same performance as LSTM while requires less training time on processing the same task. Therefore, we prefer GRU in our deep learning model.

To detect clone pairs, we propose to use a Siamese architecture neural network [10] which is best suited for similarity comparison of two objects. Siamese neural network is a class of neural network architectures that contains two identical subnetworks, which means that they have the same configuration with the same parameters and weights. It has been widely applied in many areas, such

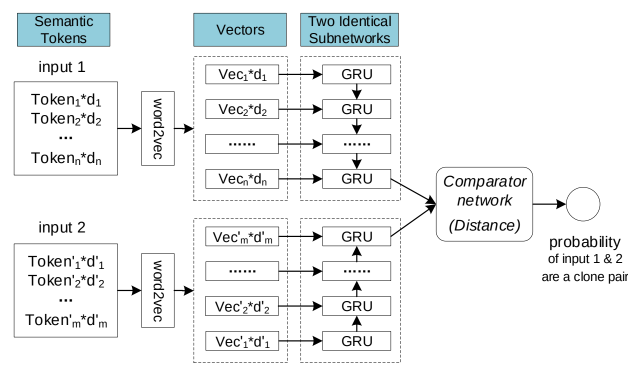


**Figure 4: Siamese architecture of *SCDetector***

as paraphrase scoring, where the inputs are two sentences and the output is a score of how similar they are. One important characteristic of using Siamese neural network is that the data set can be enlarged by using pairs of inputs instead of single ones. Given $n$ samples of a class, there will be $n * (n-1)/2$ positive pairs and many negative pairs. Another advantage of Siamese network is that sharing weights across subnetworks making it require fewer parameters to train for than a plain architecture with the same number of layers.

Figure 4 presents the Siamese architecture neural network used in *SCDetector*. The two identical subnetworks are two GRU neural networks sharing the same weights. The inputs of a GRU network are certain semantic tokens (*i.e.,* tokens with total degree centrality) obtained by centrality analysis. We first train embeddings of tokens using word2vec [38] to convert a token into a fix-length vector whose dimension is set to be 100. After multiplying by the corresponding total degree centrality, the semantic vectors are then fed into two identical GRU subnetworks. The purpose of a one-layer GRU subnet is to learn the mapping from the variable-length sequence space of 100-dimensional vectors to 50-dimensional. Finally, a comparator network takes inputs of these two subnetworks' outputs to compute the distance. In practice, the distance measure can be adopted from several different measures, such as *Manhattan distance* and *Cosine distance*. In the paper, we leverage *Cosine distance* as our distance measure while others can use other measures. Moreover, the loss function used in these two subnetworks to penalize the incorrect classification is cross-entropy. The Siamese network is trained using *Root Mean Square Prop* (RMSProp) with a learning rate of 0.0001. The output of the trained Siamese network is the probability that two input methods are a clone pair. We claim that two methods are a pair of clones if the value is above 0.5.

# 5 EXPERIMENTS

In this section, we aim to answer the following research questions:

- *RQ1: What is the effectiveness of SCDetector on detecting different types of code clones?*
- *RQ2: How the use of semantic tokens and Siamese network contribute to the effectiveness of SCDetector on detecting semantic code clones?*
- *RQ3: What is the time performance of SCDetector compared to other state-of-the-art clone detectors?*

## 5.1 Experimental Datasets

We conduct our evaluations on two datasets: Google Code Jam [1] and BigCloneBench [2]. Programs in Google Code Jam [1] are collected from an online programming competition held by Google. In our experiment, we use the same dataset collected by [58], which consists of 1,669 projects from 12 different competition problems. As discussed in [58], projects for solving the same problem are functionally similar while those for different problems are dissimilar. Moreover, very few projects within a competition problem are syntactically similar. Therefore, we can assume that code clone pairs in the same problem are most likely to be semantic clones (*i.e.,* Type-4 clones). The total number of similar and dissimilar method pairs are 275,570 and 1,116,376, respectively.

The second dataset used in our experiment is BigCloneBench [2] dataset, which composes of over 6,000,000 tagged clone pairs from 25,000 systems. The code granularity of clone pairs in BigCloneBench [2] is also function-level, and each clone pair is manually assigned a corresponding clone type. Because of the ambiguous boundary between Type-3 and Type-4, these two clone types are further divided into three subcategories by a similarity score measured by line-level and token-level after Type-1 and Type-2 normalizations, as follows: i) *Strongly Type-3* (ST3) with a similarity between [0.7, 1.0), ii) *Moderately Type-3* (MT3) with a similarity between [0.5, 0.7), and iii) *Weakly Type-3/Type-4* (WT3/T4) with a similarity between [0.0, 0.5).

## 5.2 Experimental Settings

For static analysis, we leverage a java optimization framework (*i.e., Soot* [3]) to generate the CFG of each method. Before obtaining the graph representation, we first need to compile the java source code into the corresponding *.class*. Then *Soot* is able to generate the CFG from the *.class*. In Google Code Jam dataset, we find that several programs report compilation errors such as '*no such file or directory*'. In order to correctly compile these programs, we then manually check them and find that the functionality of these programs is to process and analyze the data in an input file. After creating a file with the corresponding name in a program, we are able to generate the CFG. For BigCloneBench [2], because it does not provide the dependency libraries for most of the source code files, we select these successfully compiled files as our final dataset. The total number of final clone pairs is 280,390 including 8,139 Type-1 clones, 3,292 Type-2 clones, 3,469 Strongly Type-3 clones, 7,606 Moderately Type-3 clones, and 256,857 Weakly Type-3/Type-4 clones. Because of the lack of false tagged clone pairs in our BigCloneBench dataset, we randomly choose 280,000 dissimilar pairs from Google Code Jam dataset to complete the training and testing phase. For centrality analysis, we use a python library, *networkx* [5] to extract the degree centrality of all basic blocks in a CFG. Moreover, the Siamese neural network is implemented with *PyTorch* [6].

**Table 2: Descriptions of used metrics in our experiments**

| Metrics | Abbr | Definition |
|---|---|---|
| True Positive | **TP** | #samples correctly classified as clone pairs |
| True Negative | **TN** | #samples correctly classified as dissimilar pairs |
| False Positive | **FP** | #samples incorrectly classified as clone pairs |
| False Negative | **FN** | #samples incorrectly classified as dissimilar pairs |
| Precision | **P** | TP/(TP+FP) |
| Recall | **R** | TP/(TP+FN) |
| F-measure | **F1** | 2*P*R/(P+R) |

There has been proposed many approaches to detect code clones such as Iman [31], Rochelle [15], Toshihiro [27], Lingxiao [25], Abdullah [44], Raghavan [34], Jens [32], and Min [50]. However, most of them are not open-source. Therefore, We only compare *SCDetector* with the following state-of-the-art clone detection approaches:

- ***SourcererCC*** [43]: a state-of-the-art token-based clone detection tool.
- ***Deckard*** [24]: a popular AST-based clone detector.
- ***RtvNN*** [53]: a RNN-based clone detector that operates on source code tokens and ASTs.
- ***ASTNN*** [57]: a state-of-the-art deep learning-based functional clone detector that applies GRU on ASTs.

We run all experiments on a server with 8 cores of CPU and a GTX 1080 GPU. For both datasets, we first randomly divide them into ten subsets, then the seven subsets are used to train a model, the other two subsets are used to validate, and the last subset is used to test. We totally conduct five times and report the average results in our evaluations. Moreover, the widely used metrics to measure the detection performance are illustrated in Table 2.

## 5.3 RQ1: Overall Effectiveness

5.3.1 *Results on Google Code Jam.* As mentioned before, projects in Google Code Jam for solving the same problem are functionally similar, and very few projects within a competition problem are syntactically similar. Therefore, code clone pairs in the same problem are most likely to be semantic clones (*i.e.,* Type-4 clones). In the paper, we assume that Google Code Jam dataset is a semantic code clone dataset and conduct experiments to examine the effectiveness of *SCDetector* on semantic clones detection.

Since the dataset used in this evaluation is the same as in [58], we directly adopt the results of *Deckard* [24] and *RtvNN* [53] as reported in [58]. Table 3 shows the detection results of *SourcererCC* [43], *Deckard* [24], *RtvNN* [53], and *SCDetector*. We ignore the result of *ASTNN* [57] because it takes a lot of time and some errors occur when processing code pairs in Google Code Jam dataset.

**Table 3: Results on Google Code Jam dataset**

| | Recall | Precision | F1 |
|---|---|---|---|
| SourcererCC | 0.11 | 0.43 | 0.17 |
| Deckard | 0.44 | 0.45 | 0.44 |
| RtvNN | **0.90** | 0.20 | 0.33 |
| SCDetector | 0.87 | **0.81** | **0.82** |

*SourcererCC* achieves low recall and precision. It is reasonable that *SourcererCC* only considers the overlap similarity of tokens between two methods. As discussed in section 2, given two methods $M_1$ and $M_2$, the overlap similarity $S(M_1, M_2)$ is calculated as the ratio between the number of same tokens shared by $M_1$ and $M_2$ and the maximum number of tokens in $M_1$ and $M_2$. Therefore, it can not handle semantic clones because of the lack of consideration of program semantics.

*Deckard* clusters the characteristic vectors of each AST subtree using predefined rules of two methods to detect clones. However, we find that more than half of the code clone pairs for solving the same competition problem have diverse parser tree structures, resulting in low precision and recall when detecting clones in Google Code Jam dataset.

*RtvNN* is able to achieve the highest recall but very low precision. After we manually check the detected pairs, we find that almost all the code pairs (*i.e.,* similar pairs and dissimilar pairs) are detected as clones. It is because two functionally dissimilar methods may share syntactically similar components (*i.e.,* IO operations) while *RtvNN* can not handle these issues. As discussed in [58], the distances between most methods calculated by *RtvNN* are in the range of [2.0, 2.8]. By lowering the distance threshold, the precision of *RtvNN* can be increased to 90%, however, its recall also drops quickly (down to less than 10%). As a result, it can only achieve 0.325 F1 score at the highest.

In conclusion, *SCDetector* is able to handle most of semantic code clones in Google Code Jam dataset compared to *SourcererCC*, *Deckard*, and *RtvNN*.

*5.3.2 Results on BigCloneBench.* On the one hand, prior work has validated that graph-based clone detectors can handle certain semantic clones. On the other hand, experimental results in a recent study (*i.e., ASTNN* [57]) have verified that *ASTNN* [57] is superior to *program dependency graph-based* (PDG-based) methods. Therefore, we only conduct comparative experiments to *ASTNN* instead of other PDG-based methods [32, 34, 50] in this evaluation.

Table 4 and 5 present the evaluation results of *SourcererCC*, *Deckard* , *RtvNN*, *ASTNN*, and *SCDetector*. *SCDetector* outperforms all the other detectors for both recall and precision. The F1 scores are encouraging as they show that *SCDetector* is able to handle different clone types. For example, when detecting Weakly Type-3/Type-4 clones, the F1 scores of *SourcererCC*, *Deckard*, *RtvNN*, and *ASTNN* are 2%, 2%, 0%, and 92% while *SCDetector* is able to maintain 97% of F1.

**Table 4: F1 for each clone type in BigCloneBench**

| | T1 | T2 | ST3 | MT3 | WT3/T4 |
|---|---|---|---|---|---|
| SourcererCC | 1.00 | 1.00 | 0.65 | 0.20 | 0.02 |
| Deckard | 0.73 | 0.71 | 0.54 | 0.21 | 0.02 |
| RtvNN | 1.00 | 0.97 | 0.60 | 0.03 | 0.00 |
| ASTNN | 1.00 | 1.00 | 0.99 | 0.98 | 0.92 |
| SCDetector | **1.00** | **1.00** | **0.99** | **0.99** | **0.97** |

**Table 5: Results on BigCloneBench dataset**

| | Recall | Precision | F1 |
|---|---|---|---|
| SourcererCC | 0.07 | 0.98 | 0.14 |
| Deckard | 0.06 | 0.93 | 0.12 |
| RtvNN | 0.01 | 0.95 | 0.01 |
| ASTNN | 0.94 | 0.92 | 0.93 |
| SCDetector | **0.97** | **0.98** | **0.98** |

As a matter of fact, the recall, precision, and F1 scores of *SCDetector* are higher than those on Google Code Jam dataset. To find out the reason why *SCDetector* performs better on BigCloneBench dataset, we manually examine several Type-4 clone pairs from BigCloneBench dataset and Google Code Jam dataset, respectively. The inspection results show that many of clone pairs in BigCloneBench share similar code structure while only differ on the sequence of the invoked API calls because these clone pairs are intentionally constructed by several experts. However, programs in Google Code Jam dataset are all implemented by different students or other programmers from scratch. Therefore, they are more difficult to be detected as a clone pair in Google Code Jam dataset compared to BigCloneBench dataset.

In conclusion, *SCDetector* has the ability to detect different types of code clones.

## 5.4 RQ2: Semantic Tokens and Siamese Network

In order to check the effectiveness of semantic tokens and Siamese network on detecting semantic clones, we conduct several single factor experiments. In the first experiment, we take inputs of the original tokens obtained from the source code of a method by lexical analysis into a GRU encoder. Given two methods, the outputs of the GRU encoder are two vectors. After obtaining the similarity (*i.e.,* normalization) of two vectors by analyzing the *Cosine distance* between them, we claim that the two methods are a clone pair when the similarity is greater than 70%. In our second experiment, the original tokens are fed into a Siamese network including two identical GRU subnetworks. The output of the Siamese network is the probability that two input methods are a clone pair. Two methods are detected as a clone pair if the probability is larger than 0.5. In our final experiment, we implement *SCDetector*, which means that methods are first transformed into certain semantic tokens (*i.e.,* tokens with the total degree centrality) and then fed into a Siamese GRU network to train and test. Similarly, if the probability is larger than 0.5, these two methods are treated as a clone pair. GRU networks used in these three experiments are the same networks.

**Table 6: Results on Google Code Jam dataset**

| | Recall | Precision | F1 |
|---|---|---|---|
| GRU-OriginalTokens | 0.29 | 0.25 | 0.27 |
| Siamese-GRU-OriginalTokens | 0.72 | 0.55 | 0.53 |
| Siamese-GRU-SemanticTokens (*SCDetector*) | **0.87** | **0.81** | **0.82** |

Table 6 presents the detection results including recall, precision, and F1 of our three single factor experiments on Google Code Jam dataset. Such results indicate that *SCDetector* is able to perform best because of the preservation of graph semantics (*i.e.,* CFG) and the utilization of a Siamese network. For instance, when we only input the original tokens obtained from the source code of a method by lexical analysis into a GRU encoder to detect clones, the F1 is only 27%. However, the F1 is able to maintain 53% when we adopt a Siamese network to further process the original tokens. We find that the improvements are mainly because the Siamese network can adjust the differences between functional similar methods. Given two methods, the Siamese network first maps the input pair to the same feature space. If the pair is a clone pair, the distance between them will be adjusted to be smaller as possible with training. On the contrary, if it is not a clone pair, the distance will be adjusted larger and larger. As a matter of fact, clones in Google Code Jam dataset are implemented by different programmers from scratch, thus these semantic clones are almost syntactically different. If we only use a GRU network to encode a method into a vector representation and then compute the similarity to identify clones, it is generally difficult to detect such clones since they are almost syntactically different. However, when we apply a Siamese network to train and detect clones, the distance of these semantic clone pairs will be adjusted to become smaller as the training progresses, making it possible to detect such clones.

Additionally, if we first transform the graph details into semantic tokens, and then feed these semantic tokens into a Siamese GRU network to train and detect clones, the F1 is able to increase to 82%. This happens mainly due to the consideration of graph details. As discussed in Section 2, we present a clone pair which is to calculate the greatest common divisor of two integers. They belong to semantic clone since they implement the same functionality with syntactically dissimilar code. When we compute the overlap similarity by using original tokens, the pair can not be detected by *SourcererCC*. This is because these two methods are implemented in a completely different way, thus it is difficult to be detected if we only consider the original tokens. Figure 1 shows the two CFGs and we can see that these two graphs are structurally similar since they are designed to achieve the same functionality. In other words, semantic clones may share some similar subgraphs when we distill the semantics into a graph representation. Therefore, when we attach the graph details to tokens, these semantic tokens can be more effective than using original tokens on semantic clone detection.

In conclusion, the attachment of graph details to tokens and the adoption of a Siamese network are both effective on detecting code clones.

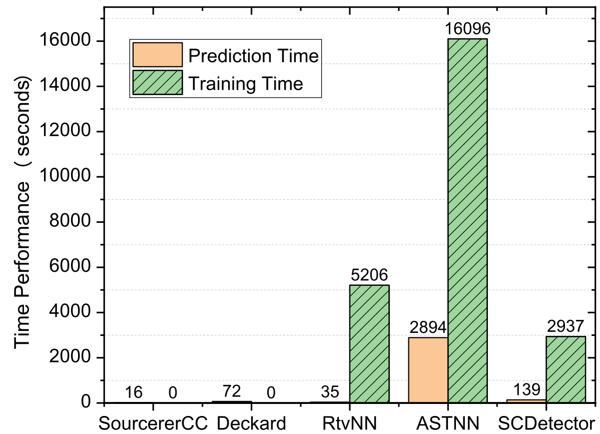


**Figure 5: Time performance of *SourcererCC, Deckard, RtvNN, ASTNN,* and *SCDetector***

## 5.5 RQ3: Scalability

In this part, we pay attention to the runtime performance of *SCDetector* and four comparative systems. In order to test the scalability of these clone detectors, we randomly select 1,000,000 code pairs from Google Code Jam dataset as our test objects. We run all tools on these randomly selected code pairs three times and report the average runtime. For deep learning-based methods, the complete procedure consists of model training and model testing. For example, the clone detection procedure of *ASTNN* consists of GRU training and GRU testing while *SCDetector* composes of Siamese network training and Siamese network testing. Therefore, in Figure 5, we present the training time and prediction time of *RtvNN*, *ASTNN*, and *SCDetector* separately.

For *SourcererCC* and *Deckard*, they do not need to conduct the training phase so the training runtime overheads are both zero. In addition, *SourcererCC* takes the least time to detect clones because it is a pure token-based clone detector. Compared to *RtvNN*, *SCDetector* takes less time to train while requires more time to detect code clones. However, from the experimental results in Table 3, 4, and 5, we can see that the ability of *RtvNN* on semantic clone detection is very low. Moreover, as for *ASTNN*, results in Figure 5 report that *SCDetector* is more scalable than *ASTNN* not only on training phase but also on testing phase. The training time and testing time of *ASTNN* are 16,096 seconds and 2,894 seconds while *SCDetector* only needs to take 3,076 seconds (*i.e.,* 2,937 seconds for training and 139 seconds for testing) to complete the whole clone detection. It is reasonable because the number of hidden layers in *SCDetector* is only one which requires less time to train and test.

*SCDetector* aims to balance the ability of token-based and graph-based techniques to detect semantic clones. As for token-based methods, *SourcererCC* is the most scalable tool that can scale to very big code and we have presented the runtime overhead in Figure 5. As for graph-based approaches, we select one state-of-the-art traditional graph-based clone detection tool namely *CCSharp* [50] to compare the scalability. *CCSharp* aims to solve the problem of PDG-based tools' high time cost. It adopts two strategies (*i.e.,* PDG's structure modification and characteristic vector filtering) to decrease the overall computing quantity. *CCSharp* is not open-source and we can not test it on Google Code Jam dataset. However, they present the scale of their dataset and report the time performance in their paper. Table 7 shows the details of two datasets including the total *lines of code* (LOC), the total number of methods, and the time performance. Obviously, our randomly selected 1 million pairs are larger than the dataset in *CCSharp*. *CCSharp* does not need to train, thus the training time is zero. In reality, the training phase of *SCDetector* is the most time-consuming process, however, it is a one-time offline phase. Once the model is trained, it can be reused to compute the code similarity between two given methods. Compared to *CCSharp*, the prediction time of *SCDetector* is extremely less than *CCSharp*. The runtime overhead on detecting clones is 1,995.9 seconds for *CCSharp* while is 139 seconds for *SCDetector* when given a trained model. In other words, given a trained model, *SCDetector* is 14 times faster than *CCSharp*.

**Table 7: The scale of datasets used in *CCSharp* and our evaluation**

| Dataset | LOC | #methods | Training Time | Prediction Time |
|---|---|---|---|---|
| PostgreSQL in *CCSharp* [50] | 86,096 | 1,134 | 0 | 1,995.9 |
| Google Code Jam (1 million pairs) | 98,117 | 1,669 | 2,937 | 139 |

In summary, because of the consideration of graph details and the adoption of deep learning, *SCDetector* requires more time to detect clones compared to a token-based method (*i.e., SourcererCC*). However, compared to a graph-based method (*i.e., CCSharp*), *SCDetector* is 14 times faster due to the transformation of graph details.

## 6 DISCUSSIONS

***Differences from the most similar systems.*** The most similar related methods to *SCDetector* are *Oreo* [42] and *Centroid* [12]. *Oreo* also applies a Siamese network to detect clones, however, the inputs of its Siamese network are 24 method-level software metrics while are certain semantic tokens in *SCDetector*. Moreover, since *SCDetector* takes inputs of semantic tokens, we leverage two identical one-layer GRU subnetworks to measure the distance between them. As for *Oreo*, the Siamese network consists of two four-layer DNN subnetworks, which are different from *SCDetector*. *Centroid* aims to detect application clones on Android markets, it uses a geometry characteristic, called centroid, of CFGs to measure the similarity of methods in two apps. The graph representation of *Centroid* is the same as *SCDetector*, that is, a CFG of a method. In physics, especially when analyzing forces on a physical object, people usually use the center of mass (*i.e.,* centroid) to represent an object. When two objects are identical, their centroids are also the same. In *SCDetector*, we regard the CFG of a method as a social network and apply social-network-centrality analysis to extract the degree centrality of all basic blocks. Although the graph representations of *Centroid* and *SCDetector* are the same, the perspective of graph analysis is completely different, that is, the physical analysis of *Centroid* and the social network analysis of *SCDetector*.

***Why SCDetector outperforms the other approaches.*** The reasons are mainly two-fold. First, *SCDetector* considers the program semantics by transforming the CFG of a method into corresponding semantic tokens. These tokens are used to measure code similarity of different methods. However, traditional token-based techniques (*e.g., CCFinder* [28] and *SourcererCC* [43]) have no ability to handle semantic clones since they only care about syntactic level's code features rather than semantic level's details because of the high time cost of the semantic analysis process. Second, we apply a Siamese network in *SCDetector* to train and detect code clones. Siamese network is best suited for similarity comparison of two objects. Given two methods, it first maps the input pair to the same feature space. If they are not a clone pair, the distance between them will be adjusted larger and larger as the training progresses. On the contrary, if the pair is a clone pair, the distance will be adjusted to become smaller with training, making it possible to detect semantic clones. Through our experimental results, we can see that the Siamese network can indeed improve the detection effectiveness. However, as for *RtvNN* [53] and *ASTNN* [57], after obtaining the vector representations, they compute the similarity directly, making them perform worse than *SCDetector*.

## 7 LIMITATIONS

First, the key insight of *SCDetector* is to transform the CFG of a method into tokens with graph details. Therefore, we need to obtain the graph representation first by static analysis. Because the experimental datasets are implemented in *Java*, we leverage a java optimization framework, namely *Soot* [3] to complete our static analysis phase. However, *Soot* [3] requires to successfully compile the given codes first and then the CFG can be extracted. It is the reason why we can not use all the files in BigCloneBench dataset to commence our evaluations. In our future work, we plan to implement a static analysis tool or leverage other static analysis tools (*e.g., WALA* [7]) to generate the CFG of methods from source code directly.

Second, *SCDetector* extracts the CFG of a method and detects clone by measuring the similarity of methods. Therefore, *SCDetector* can only detect method-level code clones and can not handle clones in other code granularity units (*e.g.,* line-level). Moreover, copying a method and then pasting with large number of edits can cause false negatives by *SCDetector* since the CFGs of the original method and the pasted method are significantly different. Such clones are considered as large-gap clones in [51]. We plan to combine other network properties with centrality to mitigate the issue.

Third, *SCDetector* is based on the degree centrality of tokens and relies on the common tokens between two programs. Although the extraction of a CFG from a method source code by *Soot* can normalize several tokens, *SCDetector* may cause false negatives when the same functionality is implemented using different APIs and different graph structures. We plan to normalize the source code first and then conduct static analysis to generate abstracted CFGs for more effective comparison.

Fourth, we generate semantic tokens by analyzing the degree centrality of all basic blocks in a CFG since the extraction of degree centrality is the most efficient among several different centrality measures [54]. However, degree centrality reflects the relative number of connections of a node in a CFG and is limited in representing the graph context. We plan to use more different centrality measures to find the most suitable centrality that can balance the effectiveness and the efficiency on code clone detection.

Fifth, since the input of our Siamese network in *SCDetector* is semantic tokens, *SCDetector* may cause false positives when methods realize different functionalities based on some unique tokens while having a very similar structure. The most critical operations of these methods are different, resulting in completely different semantics. *SCDetector* can not handle this type of code clones. We plan to combine the attention [49] with the centrality of all tokens to mitigate the situation.

Sixth, the degree centrality can quantify the importance of tokens in a CFG. In *SCDetector*, the purpose of degree centrality extraction is to maintain the graph details to achieve a semantic code comparison. High degree centrality does not indicate high impact on our final comparison results. In our GRU network, the inputs of semantic tokens are simply sorted according to the first letter. We plan to analyze the tokens in the source code first to obtain more accurate orders of all tokens.

## 8 RELATED WORK

In this part, we introduce studies related to code clone detection, which can be classified into five main categories, as follows: the text-based, the token-based, the tree-based, the graph-based, and the metrics-based methods.

For the text-based methods [14, 26, 40], the similarity between two code snippets are measured in the form of text or strings. [26] designs a fingerprinting technique to find out code clones. [14] presents a language-independent method to detect similar codes by simply line-based string matching. However, these two techniques do not support Type-3 clone detection. In order to detect more types of clones, *Nicad* [40] introduces a two-stage approach which consists of i) identification and normalization of potential clones using flexible pretty-printing and ii) similarity computation by simply text-line comparison using longest common subsequence algorithm. Although *Nicad* can detect several Type-3 clones, it has no ability to handle Type-4 clones since it ignores the program semantics of given code fragments.

For the token-based techniques [20, 28, 35, 43, 51], tokens are firstly obtained from program code by lexical analysis. *CCFinder* [28] extracts a token sequence from the input code and applies several rule-based transformations to convert the token sequence into a regular form for detecting Type-1 and Type-2 clones. In order to support Type-3 clone detection, *SourcererCC* [43] has been designed. It captures the tokens' overlap similarity among different methods to detect near-miss Type-3 clones. *SourcererCC* [43] is the most scalable code clone detector which can scale to 250M line code clone detection. However, similar to text-based methods, token-based approaches can not handle Type-4 clones either.

For the tree-based tools [24, 52, 57], *Abstract Syntax Tree* (AST) is used as the code representation to detect code clones. The main idea of *Deckard* [24] is to compute characteristic vectors within ASTs and apply *Locality Sensitive Hashing* (LSH) to cluster similar vectors for clone detection. *CDLH* [52] first transforms ASTs into binary trees and then adopts Tree-LSTM [46] on these trees to encode them as vector representations. Finally, these vectors are used to measure the similarity among different codes. Unlike *CDLH* [52], *ASTNN* [57] splits each large AST into a sequence of small statement trees. After encoding these statement trees into vectors, a bidirectional RNN model is used to produce the final vector representation of a code fragment to discover semantic code clones. These tree-based tools are able to detect semantic clones, however, they suffer from low scalability because of the large execution times.

For the graph-based methods [12, 32, 34, 50, 58], program semantics are firstly distilled into different graph representations, such as program dependency graph and control flow graph. [32] and [34] both extract the program dependency graphs of code fragments and identify similar codes by digging out isomorphic subgraphs to represent code clones. In an effort to improve the runtime performance of [32] and [34], *CCSharp* [50] adopts two strategies to mitigate the overall computing cost: graph structure modification and characteristic vector filtering. However, it still suffers from low scalability on large-scale code clone detection due to the complexity of graph isomorphism and heavy-weight time consumption of graph matching.

For the metrics-based approaches [9, 37, 39, 42], metrics can be obtained from tree or graph representations of source code or directly from source code. Both [9] and [37] extract metrics from AST to represent the source code and uses them to identify code clones. In addition, [39] uses different categories of metrics (*e.g.,* classes, coupling, and hierarchical structure) extracted from source code to detect clones. These methods leverage features from code to measure the semantic similarity of two code fragments.

## 9 CONCLUSION

In this paper, we propose a novel method to measure the similarity of semantic codes, namely *SCDetector*. *SCDetector* is a combination of token-based and graph-based approach. Given a method source code, we first generate the CFG and then apply centrality analysis to transform the graph into certain semantic tokens (*i.e.,* tokens with graph details). Finally, these semantic tokens are fed into a Siamese network to train a model and use it to detect code clone pairs. We evaluate *SCDetector* on two widely used datasets and experimental results show that *SCDetector* is superior to other four state-of-the-art clone detectors (*i.e., SourcererCC* [43], *Deckard* [24], *RtvNN* [53], and *ASTNN* [57]). Moreover, the time cost of *SCDetector* is 14 times less than a traditional graph-based method (*i.e., CCSharp* [50]).

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## References

[1] 2017. Google Code Jam. https://code.google.com/codejam/past-contests.

[2] 2020. BigCloneBench. https://github.com/clonebench/BigCloneBench.
[3] 2020. A Java optimization framework (Soot). https://github.com/Sable/soot.
[4] 2020. Platform for C/C++ Code Analysis (Joern). https://joern.io.
[5] 2020. Software for complex networks (Networkx). http://networkx.github.io.
[6] 2020. Tensors and Dynamic neural networks in Python with strong GPU acceleration (PyTorch). https://pytorch.org.
[7] 2020. T.J. Watson Libraries for Analysis (WALA). http://wala.sourceforge.net/wiki/index.php/Main_Page.
[8] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2014. Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473* (2014).
[9] Magdalena Balazinska, Ettore Merlo, Michel Dagenais, Bruno Lague, and Kostas Kontogiannis. 1999. Measuring clone based reengineering opportunities. In *Proceedings of the 6th International Software Metrics Symposium (ISMS'99)*. 292–303.
[10] Pierre Baldi and Yves Chauvin. 1993. Neural networks for fingerprint recognition. *Neural Computation* 5, 3 (1993), 402–418.
[11] Stefan Bellon, Rainer Koschke, Giulio Antoniol, Jens Krinke, and Ettore Merlo. 2007. Comparison and evaluation of clone detection tools. *IEEE Transactions on Software Engineering* 33, 9 (2007), 577–591.
[12] Kai Chen, Peng Liu, and Yingjun Zhang. 2014. Achieving accuracy and scalability simultaneously in detecting application clones on android markets. In *Proceedings of the 36th International Conference on Software Engineering (ICSE'14)*. 175–186.
[13] Nigel Coles. 2001. It's not what you know—It's who you know that counts. Analysing serious crime groups as social networks. *British Journal of Criminology* 41, 4 (2001), 580–594.
[14] Stéphane Ducasse, Matthias Rieger, and Serge Demeyer. 1999. A language independent approach for detecting duplicated code. In *Proceedings of the 1999 International Conference on Software Maintenance (ICSM'99)*. 109–118.
[15] Rochelle Elva and GT. Leavens. 2012. *Jsctracker: A semantic clone detection tool for java code.* Technical Report. University of Central Florida.
[16] Katherine Faust. 1997. Centrality in affiliation networks. *Social Networks* 19, 2 (1997), 157–191.
[17] LC. Freeman. 1977. A set of measures of centrality based on betweenness. *Sociometry* 40, 1 (1977), 35–41.
[18] LC. Freeman. 1978. Centrality in social networks conceptual clarification. *Social Networks* 1, 3 (1978), 215–239.
[19] DM. German, Massimiliano Di Penta, Yann-Gael Gueheneuc, and Giuliano Antoniol. 2009. Code siblings: Technical and legal implications of copying code between applications. In *Proceedings of the 6th International Working Conference on Mining Software Repositories (MSR'09)*. 81–90.
[20] Nils Göde and Rainer Koschke. 2009. Incremental clone detection. In *Proceedings of the 2009 European Conference on Software Maintenance and Reengineering (ECSMR'09)*. 219–228.
[21] Roger Guimera, Stefano Mossa, Adrian Turtschi, and LA Nunes Amaral. 2005. The worldwide air transportation network: Anomalous centrality, community structure, and cities' global roles. *the National Academy of Sciences* 102, 22 (2005), 7794–7799.
[22] Tomoya Ishihara, Keisuke Hotta, Yoshiki Higo, Hiroshi Igaki, and Shinji Kusumoto. 2012. Inter-project functional clone detection toward building libraries: an empirical study on 13,000 projects. In *Proceedings of the 19th Working Conference on Reverse Engineering (WCRE'12)*. 387–391.
[23] Hawoong Jeong, SP. Mason, AL. Barabási, and ZN. Oltvai. 2001. Lethality and centrality in protein networks. *Nature* 411, 6833 (2001), 41–42.
[24] Lingxiao Jiang, Ghassan Misherghi, Zhendong Su, and Stephane Glondu. 2007. Deckard: Scalable and accurate tree-based detection of code clones. In *Proceedings of the 29th International Conference on Software Engineering (ICSE'07)*. 96–105.
[25] Lingxiao Jiang and Zhendong Su. 2009. Automatic mining of functionally equivalent code fragments via random testing. In *Proceedings of the 18th International Symposium on Software Testing and Analysis (ISSTA'09)*. 81–92.
[26] J Howard Johnson. 1994. Substring matching for clone detection and change tracking. In *Proceedings of the 1994 International Conference on Software Maintenance (ICSM'94)*. 120–126.
[27] Toshihiro Kamiya. 2013. Agec: An execution-semantic clone detection tool. In *Proceedings of the 21st International Conference on Program Comprehension (ICPC'13)*. 227–229.
[28] Toshihiro Kamiya, Shinji Kusumoto, and Katsuro Inoue. 2002. CCFinder: A multilinguistic token-based code clone detection system for large scale source code. *IEEE Transactions on Software Engineering* 28, 7 (2002), 654–670.
[29] Leo Katz. 1953. A new status index derived from sociometric analysis. *Psychometrika* 18, 1 (1953), 39–43.
[30] Iman Keivanloo, Juergen Rilling, and Philippe Charland. 2011. Internet-scale real-time code clone search via multi-level indexing. In *Proceedings of the 18th Working Conference on Reverse Engineering (WCRE'11)*. 23–27.
[31] Iman Keivanloo, CK. Roy, and Juergen Rilling. 2012. Sebyte: A semantic clone detection tool for intermediate languages. In *Proceedings of the 20th International Conference on Program Comprehension (ICPC'12)*. 247–249.
[32] Raghavan Komondoor and Susan Horwitz. 2001. Using slicing to identify duplication in source code. In *Proceedings of the 2001 International Static Analysis Symposium (ISAS'01)*. 40–56.
[33] Rainer Koschke. 2012. Large-scale inter-system clone detection using suffix trees. In *Proceedings of the 16th European Conference on Software Maintenance and Reengineering (ECSME'12)*. 309–318.
[34] Jens Krinke. 2001. Identifying similar code with program dependence graphs. In *Proceedings of the 8th Working Conference on Reverse Engineering (WCRE'01)*. 301–309.
[35] Liuqing Li, He Feng, Wenjie Zhuang, Na Meng, and Barbara Ryder. 2017. CClearner: A deep learning-based clone detection approach. In *Proceedings of the 2017 International Conference on Software Maintenance and Evolution (ICSME'17)*. 249–260.
[36] Xiaoming Liu, Johan Bollen, ML. Nelson, and Herbert Van de Sompel. 2005. Co-authorship networks in the digital library research community. *Information Processing & Management* 41, 6 (2005), 1462–1480.
[37] Jean Mayrand, Claude Leblanc, and Ettore Merlo. 1996. Experiment on the automatic detection of function clones in a software system using metrics. In *Proceedings of the 1996 International Conference on Software Maintenance (ICSM'96)*. 244–253.
[38] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781* (2013).
[39] JF. Patenaude, Ettore Merlo, Michel Dagenais, and Bruno Laguë. 1999. Extending software quality assessment techniques to java systems. In *Proceedings of the 7th International Workshop on Program Comprehension (IWPC'99)*. 49–56.
[40] CK. Roy and JR. Cordy. 2008. NICAD: Accurate detection of near-miss intentional clones using flexible pretty-printing and code normalization. In *Proceedings of the 2008 International Conference on Program Comprehension (ICPC'08)*. 172–181.
[41] Chanchal Kumar Roy and JR. Cordy. 2007. A survey on software clone detection research. *Queen's School of Computing TR* 541, 115 (2007), 64–68.
[42] Vaibhav Saini, Farima Farmahinifarahani, Yadong Lu, Pierre Baldi, and Cristina V Lopes. 2018. Oreo: Detection of clones in the twilight zone. In *Proceedings of the 26th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (FSE'18)*. 354–365.
[43] Hitesh Sajnani, Vaibhav Saini, Jeffrey Svajlenko, CK. Roy, and CV. Lopes. 2016. SourcererCC: Scaling code clone detection to big code. In *Proceedings of the 38th International Conference on Software Engineering (ICSE'16)*. 1157–1168.
[44] Abdullah Sheneamer and Jugal Kalita. 2016. Semantic clone detection using machine learning. In *Proceedings of the 15th International Conference on Machine Learning and Applications (ICMLA'16)*. 1024–1028.
[45] Jeffrey Svajlenko, JF. Islam, Iman Keivanloo, CK. Roy, and Mohammad Mamun Mia. 2014. Towards a big data curated benchmark of inter-project code clones. In *Proceedings of the 2014 International Conference on Software Maintenance and Evolution (ICSME'14)*. 476–480.
[46] Kai Sheng Tai, Richard Socher, and CD. Manning. 2015. Improved semantic representations from tree-structured long short-term memory networks. *arXiv preprint arXiv:1503.00075* (2015).
[47] Duyu Tang, Bing Qin, and Ting Liu. 2015. Document modeling with gated recurrent neural network for sentiment classification. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing (CMNLP'15)*. 1422–1432.
[48] Michele Tufano, Cody Watson, Gabriele Bavota, Massimiliano Di Penta, Martin White, and Denys Poshyvanyk. 2018. Deep learning similarities from different representations of source code. In *Proceedings of the 15th International Conference on Mining Software Repositories (MSR'18)*. 542–553.
[49] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, AN. Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Proceddings of the 2017 Conference on Neural Information Processing Systems (NIPS'17)*. 5998–6008.
[50] Min Wang, Pengcheng Wang, and Yun Xu. 2017. CCSharp: An efficient three-phase code clone detector using modified pdgs. In *Proceedings of the 24th Asia-Pacific Software Engineering Conference (APSEC'17)*. 100–109.
[51] Pengcheng Wang, Jeffrey Svajlenko, Yanzhao Wu, Yun Xu, and CK. Roy. 2018. CCAligner: A token based large-gap clone detector. In *Proceedings of the 40th International Conference on Software Engineering (ICSE'18)*. 1066–1077.
[52] Huihui Wei and Ming Li. 2017. Supervised deep features for software functional clone detection by exploiting lexical and syntactical information in source code. In *Proceedings of the 2017 International Joint Conferences on Artificial Intelligence (IJCAI'17)*. 3034–3040.
[53] Martin White, Michele Tufano, Christopher Vendome, and Denys Poshyvanyk. 2016. Deep learning code fragments for code clone detection. In *Proceedings of the 31st International Conference on Automated Software Engineering (ASE'16)*. 87–98.
[54] Yueming Wu, Xiaodi Li, Deqing Zou, Wei Yang, Xin Zhang, and Hai Jin. 2019. MalScan: Fast market-wide mobile malware scanning by social-network centrality analysis. In *Proceedings of the 34th International Conference on Automated Software Engineering (ASE'19)*. 139–150.

[55] Wei Yang, Xusheng Xiao, Benjamin Andow, Sihan Li, Tao Xie, and William Enck. 2015. Appcontext: Differentiating malicious and benign mobile app behaviors using context. In *Proceedings of the 37th International Conference on Software Engineering (ICSE'15)*. 303–313.

[56] Wojciech Zaremba and Ilya Sutskever. 2014. Learning to execute. *arXiv preprint arXiv:1410.4615* (2014).

[57] Jian Zhang, Xu Wang, Hongyu Zhang, Hailong Sun, Kaixuan Wang, and Xudong Liu. 2019. A novel neural source code representation based on abstract syntax tree. In *Proceedings of the 41st International Conference on Software Engineering (ICSE'19)*. 783–794.

[58] Gang Zhao and Jeff Huang. 2018. Deepsim: Deep learning code functional similarity. In *Proceedings of the 26th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (FSE'18)*. 141–151.