An Automated Approach to Assess the Similarity of GitHub Repositories

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Abstract. Open source software (OSS) allows developers to study, change, and improve the code free of charge. There are several high quality software projects which deliver stable and well-documented products. Most OSS forges typically sustain active user and expert communities which in turn provide decent levels of support both with respect to answering user questions as well as to repairing reported software bugs. Code reuse is an intrinsic feature of OSS, and developing a new system by leveraging existing open source components can reduce development effort, and thus it can be beneficial to at least two phases of the software life cycle, i.e., implementation and maintenance. However, to improve software quality, it is essential to develop a system by learning from well-defined, mature projects. In this sense, the ability to find similar projects that facilitate the undergoing development activities is of highly importance. In this paper, we address the issue of mining open source software repositories to detect similar projects, which can be eventually reused by developers. We propose CrossSim as a novel approach to model the OSS ecosystem and to compute similarities among software projects. An evaluation on a dataset collected from GitHub shows that our proposed approach outperforms three well-established baselines.

Keywords: Mining Software Repositories; Software Similarity; Software Quality; SimRank

1 Introduction

Open source software (OSS) repositories contain a large amount of data, which can be of high-value when developing new software systems without reimplementing already in place functionalities. The benefits resulting from the reuse of properly selected open source projects are manyfold including the fact that the system being implemented relies on open source code, *"which is of higher quality than the custom-developed code's first incarnation"* [49]. In addition to source code, also metadata available from different related sources, e.g., communication channels and bug tracking systems, can be beneficial to the development process if properly mined [43].

Mining OSS repositories: In recent years, considerable effort has been made in the domain of mining software repositories to conceive techniques and tools to help developers mine and cope with the large amount of data available in OSS repositories. The

main goal is to support software developers by providing them with meaningful recommendations. This is synthesized by relying on existing systems and past experiences. For instance, when a developer works on a new project, it is possible to provide her with suggestions about which libraries she should use, based on a comparison with other similar projects [36],[51]. Moreover, it is possible to empower IDEs by means of tools that continuously monitor the developer's activities and contexts in order to activate dedicated recommendation engines [43]. In the scope of the CROSSMINER project,[1] we aim at supporting the development of complex software systems by *(i)* enabling monitoring, in-depth analysis and evidence-based selection of open source components, and *(ii)* facilitating knowledge extraction from large OSS repositories [2]. We attempt to support software developers by means of an advanced Eclipse-based IDE providing intelligent recommendations that go far beyond the current *code completion-oriented* practice. To this end, metadata is curated from different OSS forges and processed to properly feed the recommendation engines [38]. By means of the augmented IDE, developers are able to select open source software and get real-time recommendations based on the conceived mining tools [35].

Software Similarity: Copying and pasting is a common practice in software development [46]. One of the main countermeasures to deal with software clone is to measure structural similarity among programs, aiming to evaluate their correctness, style as well as uniqueness [17]. The concept of similarity is a key issue in various contexts, such as detecting cloned code [14],[44],[45],[52] software plagiarism [27], or reducing test suite in model-based testing [11],[22]. Nevertheless, a globally exact definition of similarity is hard to come by since depending on the method used to compare items, various types of similarity may be identified. According to Walenstein *et al.* [56], a workable common understanding for software similarity is as follows: *"the degree to which two distinct programs are similar is related to how precisely they are alike."*

In the context of open source software, two projects are deemed to be similar if they implement some features being described by the same abstraction, even though they may contain various functionalities for different domains [32]. Given a software system being developed, we are interested in *finding a set of similar OSS projects* with respect to different criteria, such as external dependencies, application domain, or API usage [36],[39]. This type of recommendation is beneficial to the development since it allows developer to learn how similar projects are implemented. Understanding the similarities among open source software projects allows for reusing of source code and prototyping, or choosing alternative implementations [47],[60]. To aim for software quality [49], developers normally build their projects by learning from mature OSS projects having comparable functionalities [49]. Furthermore, similarity has been used as a base by both content-based and collaborative-filtering recommender systems to choose the most suitable items for a given user [47]. In this sense, it is necessary to equip software developers with suitable machinery which facilitates the similarity search process.

Nevertheless, measuring similarities among software systems has been considered as a daunting task [9],[32]. Furthermore, considering the miscellaneousness of artifacts in open source software repositories, similarity computation becomes more complicated

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[1] https://www.crossminer.org

as many artifacts and several cross relationships prevail. In this sense, choosing the right technique to compute software/projects similarity is a question that may arise at any time.

Goal of the paper: The purpose of this paper is twofold. First, we propose CROSS-SIM, an approach that allows us to represent different project characteristics belonging to different abstraction layers in a homogeneous manner, then SimRank [19], a graph algorithm is applied to compute the similarities among nodes. Second, we present a thorough literature review on various techniques for computing software similarities. In this sense, our paper has the following contributions:

- proposing a novel approach to represent the OSS ecosystem by exploiting its mutual relationships;
- developing an extensible and flexible framework for computing similarities among open source software projects; and
- validating the performance of our proposed framework by means of three different existing approaches to computing software similarities, namely MUDABLUE [15], CLAN [32], and REPOPAL [60];
- presenting a comprehensive literature review on the field of software similarity measurement.

Structure of the paper: The paper is structured into the following sections. Section 2 motivates our work by providing an introduction to three approaches for detecting similar software applications and open source projects. Section 3 brings in our proposed approach for computing similarities between OSS projects. An evaluation on a real GitHub dataset is described in Section 4. Afterwards, Section 5 presents the experimental results in detail. In Section 6, we review the most notable approaches for detecting similar software applications and open source projects. Finally, Section 7 concludes the paper and draws some perspective work.

2 Background

Having access to similar software projects is beneficial to the development process. By looking at a similar OSS project, developers learn how relevant classes are implemented, and in some certain extent, to reuse useful source code [47],[60]. Also, recommender systems rely heavily on similarity metrics to suggest suitable and meaningful items for a given item [13],[47],[51]. As a result, similarity computation among software and projects has attracted considerable interest from many research groups. In recent years, several approaches have been proposed to solve the problem of software similarity computation. Many of them deal with similarity for software systems, others are designed for computing similarities among open source software projects. Depending on the set of mined features, there are two main types of software similarity computation techniques [9]:

- *Low-level similarity*: it is calculated by considering low-level data, e.g., source code, byte code, function calls, API reference, etc.,

– *High-level similarity*: it is based on the metadata of the analysed projects e.g., similarities in readme files, textual descriptions, star events, etc. Source code is not taken into account.

This classification is used throughout this paper as a means to distinguish existing approaches with regards to the input information used for similarity computation. In this section, we provide a summary of three techniques for computing similarities among open source projects, i.e., MUDABLUE [15], CLAN [32], and REPOPAL [60].

MUDABlue Together with a tool for automatically categorizing open source repositories, Garg *et al.* [15] propose an approach for computing similarity between software projects using source code. A pre-processing stage is performed to extract identifiers such as variable names, function names, and to remove unrelated factors such as comment. With the application of Latent Semantic Analysis (LSA) [26], software is considered as a document and each identifier is considered as a word. LSA is used for extracting and representing the contextual usage meaning of words by statistical computations applied to a large corpus of text. In summary, MUDABLUE works in the following steps to compute similarities between software systems:

 (i) Extracts identifiers from source code and removes unrelated content;
 (ii) Creates an identifier-software matrix with each row corresponds to one identifier and each column corresponds to a software system;
(iii) Removes unimportant identifiers, i.e., those that are too rare or too popular;
(iv) Performs LSA on the identifier-software matrix and computes similarity on the reduced matrix using cosine similarity.

MUDABLUE has been evaluated on a database consisting of software systems written in C. The outcomes of the evaluation were compared against two existing approaches, namely GURU [31], and the SVM based method by Ugurel *et al.* [55]. The evaluation shows that MUDABLUE outperforms these observed algorithms with respect to precision and recall.

CLAN McMillan *et al.* propose CLAN, an approach for automatically detecting similar Java applications by exploiting the semantic layers corresponding to package class hierarchies [32]. CLAN works based on the document framework for computing similarity, semantic anchors, e.g., those that define the documents' features. Semantic anchors and dependencies help obtain a more precise value for similarity computation between documents. The assumption is that if two applications have API calls implementing requirements described by the same abstraction, then the two applications are more similar than those that do not have common API calls. The approach uses API calls as semantic anchors to compute application similarity since API calls contain precisely defined semantics. The similarity between applications is computed by matching the semantics already expressed in the API calls.

Using a complete software application as input, CLAN represents source code files as a term-document matrix (TDM). A TDM is used to store the features of a set of document and it is a matrix where a row corresponds to a document and a column represents a term [10]. Each cell in the matrix is the frequency that the corresponding term

appears in the document. By CLAN, a row contains a unique class or package and a column corresponds to an application. SVD is then applied to reduce the dimension of the matrix. Similarity between applications is computed as the cosine similarity between vector in the reduced matrix. CLAN has been tested on a dataset with more than $8,000$ SourceForge[2] applications and shows that it qualifies for the detection of similar applications [32].

MUDABLUE and CLAN are comparable in the way they represent software and source code components like variables, function names or API calls in a term-document matrix and then apply LSA to find the similarity and to category the softwares. However, CLAN has been claimed to help obtain a higher precision than MUDABLUE as it considers only API calls to represent software systems. As shown later in this paper, CLAN is more efficient than MUDABLUE as it produces recommendations in a much shorter time.

RepoPal In contrast to many previous studies that are generally based on source code [15],[29],[32], RepoPal [60] is a high-level similarity metric and takes only repositories metadata as its input. With this approach, two GitHub[3] repositories are considered to be similar if: *(i)* They contain similar `README.MD` files; *(ii)* They are starred by users of similar interests; *(iii)* They are starred together by the same users within a short period of time. Thus, the similarities between GitHub repositories are computed by using three inputs: readme file, stars and the time gap that a user stars two repositories.

Considering two repositories r_i and r_j, the following notations are defined: *(i)* f_i and f_j are the readme files with t being the set of terms in the files; *(ii)* $U(r_i)$ and $U(r_j)$ are the set of users who starred r_i and r_j, respectively; and *(iii)* $R(u_k)$ is the set of repositories that user u_k already starred. There are three similarity indices as follows:

Readme-based similarity The similarity between two readme files is calculated as the cosine similarity between their feature vectors f_i and f_j:

$$sim_f(r_i, r_j) = CosineSim(f_i, f_j) \tag{1}$$

Stargazer-based similarity The similarity between a pair of users u_k and u_l is defined as the Jaccard index [18] of the sets of repositories that u_k and u_l have already starred: $sim_u(u_k, u_l) = Jaccard(R(u_k), R(u_l))$. The star-based similarity between two repositories r_i and r_j is the average similarity score of all pairs of users who already starred r_i and r_j:

$$sim_s(r_i, r_j) = \frac{1}{|U(r_i)| \cdot |U(r_j)|} \sum_{\substack{u_k \in U(r_i) \\ u_l \in U(r_j)}} sim_u(u_k, u_l) \tag{2}$$

Time-based similarity It is supposed that if a user stars two repositories during a relative short period of time, then the two repositories are considered to be similar. Based on

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this assumption, given that $T(u_k, r_i, r_j)$ is the time gap that user u_k stars repositories r_i and r_j, the time-based similarity is computed as follows:

$$sim_t(r_i, r_j) = \frac{1}{|U(r_i) \cap U(r_j)|} \sum_{u_k \in U(r_i) \cap U(r_j)} \frac{1}{|T(u_k, r_i, r_j)|} \qquad (3)$$

Finally, the similarity between two projects is the product of the three similarity indices:

$$sim(r_i, r_j) = sim_f(r_i, r_j) \times sim_s(r_i, r_j) \times sim_t(r_i, r_j) \qquad (4)$$

REPOPAL has been evaluated against CLAN using a dataset of $1,000$ Java repositories [60]. Among them, 50 were chosen as queries. *Success Rate*, *Confidence* and *Precision* were used as the evaluation metrics. Experimental results in the paper show that REPOPAL produces better quality metrics than those of CLAN.

The above mentioned approaches are either low-level or high-level similarity. It is evident that each of these similarity tools is able to manage a certain set of features. Thus, they can only be applied in *prescribed contexts*, and cannot exploit additional information when this is available for similarity computation. We assume that combining various input information in computing similarities is highly beneficial to the context of OSS repositories. In other words, the ability to compute software similarity in a *flexible* manner is of highly importance. For instance, in the context of the CROSSMINER project, the required project similarity technique should be flexible enough to enable the development of different types of recommendations as introduced in Section 1. Thus, we expect a tool being capable of incorporating new features into the similarity computation without the need of modifying its internal design. To this end, we anticipate a representation model that integrates semantic relationships among various artifacts. The model should be able to consider implicit semantic relationships and intrinsic dependencies among different users, repositories, and source code by enabling similarity applications in different applicative scenarios.

In the next section, we propose a novel approach that attempts to effectively exploit the rich metadata infrastructure provided by the OSS ecosystem to compute software similarities. To validate the performance of the proposed approach, we conduct a thorough evaluation on a real dataset collected from GitHub and we compare our tool with the three similarity metrics introduced above.

3 CROSSSIM: A novel approach for computing similarities among GitHub repositories

Based on the observations in Section 2, we come to the conclusion that a representation model that incorporates various features and semantic relationships is highly beneficial to similarity computation. We find inspiration from a related field, namely Linked Data and Semantic Web [6], to realize such a model. Linked Data is a representation method that allows for the interlinking and semantic querying of data. The proliferation of Linked Data in recent years has enabled numerous applications. Two prominent
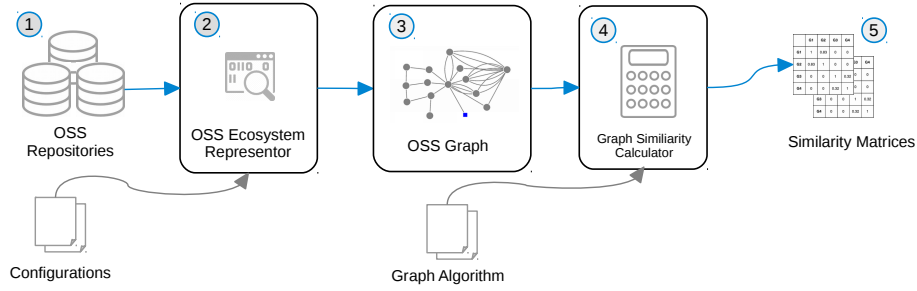
Fig. 1. Overview of the CROSSSIM approach.

examples are Linked Data for building music platform as by BBC Music [23] and for developing map application as by OpenStreetMap [50]. The core of Linked Data is an RDF[4] graph that is made up several nodes and oriented links to represent the semantic relationships among various artifacts. Thanks to this feature, the representation paves the way for various computations. One of the main applications of RDF is similarity computation for supporting recommender systems [13].

By considering the analogy of typical applications of RDF graphs and the problem of detecting the similarity of open source projects, we developed CROSSSIM (**C**ross project **R**elationships for computing **O**pen **S**ource **S**oftware **Sim**ilarity) [39], an approach that makes use of graphs for modeling different types of relationships in the OSS ecosystem [36]. Similar to RDF graphs, the representation model can capture the semantic features and considers the intrinsic connections between various actors. Specifically, the graph model has been chosen since it allows for flexible data integration and facilitates numerous similarity metrics [7]. We consider the community of developers together with OSS projects, libraries, source code, etc., and their mutual interactions as an *ecosystem*. In this system, either humans or non-human factors have mutual dependencies and implications on the others. There, several connections and interactions prevail, such as developers commit to repositories, users star repositories, or projects contain source code files, just to name a few. The graph representation allows for the computation of similarities among nodes by means of several graph algorithms.

The architecture of CROSSSIM is depicted in Figure 1. In particular, the approach imports project data from existing OSS repositories ① and represents them into a graph-based representation by means of the *OSS Ecosystem Representor* module ②. Depending on the considered repository (and thus to the information that is available for each project) the graph structure to be generated has to be properly configured. For instance in case of GitHub, specific configurations have to be specified in order to enable the representation in the target graphs of the stars assigned to each project. Such a configuration is "forge" specific and specified once, e.g., SourceForge does not provide the star based system available in GitHub. The *Graph Similarity Calculator* module ④, depending on the similarity function to be applied, computes similarity on the source graph-based representation of the input ecosystems to generate matrices ⑤ representing the similarity value for each pair of input projects.

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[4] https://www.w3.org/TR/2014/REC-rdf11-concepts-20140225/
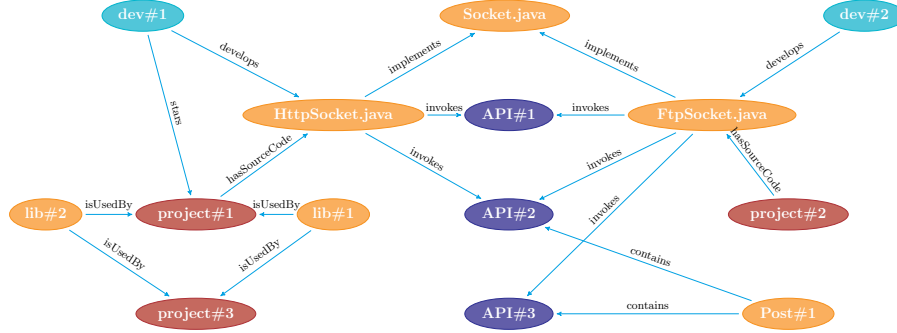
Fig. 2. A Knowledge Graph for the representation of the OSS ecosystem.

A detailed description of the proposed graph-based representation of open source projects is given in Section 3.1. Details about the implemented similarity algorithm are given in Section 3.2.

3.1 A Knowledge Graph for the OSS Ecosystem

By means of the graph representation, we transform the relationships among various artifacts in the OSS ecosystem into a mathematically computable format. The representation model considers different artifacts in a united fashion by taking into account their mutual, both direct and indirect, relationships as well as their co-occurrence as a whole.

The following relationships are used to build graphs representing the OSS ecosystems and eventually to calculate similarity exploiting the algorithm presented in the next section. These vocabularies can also be flexibly augmented upon additional features of input data, even though our current definition seems to cover the most prevailing relationships [35].

- *commits* ⊆ *Developer* × *Project*: this relationship represents the projects or libraries that a user contributes to the development;
- *contains* ⊆ *File* × *API*: a source file or a communication post with code snippets containing an API function from a third-party library;
- *extends* ⊆ *Class* × *Class*: a class inherits an abstract class. Two classes extend a same abstract class have a bond since they share a certain number of common functionalities;
- *implements* ⊆ *File* × *File*: it represents a specific relation that can occur between the source code given in two different files, e.g., a class specified in one file implementing an interface given in another file;
- *hasSourceCode* ⊆ *Project* × *File*: an OSS project contains a source file;
- *invokes* ⊆ *Class* × *API*: this is the case when a class calls an API function from a third-party library. API calls can be extracted from source files using suitable code parsers;

In the scope of this paper, we concentrate on studying the performance of CROSS-SIM by exploiting high-level information, i.e., *isUsedBy*, *develops*, and *stars*, which are described as follows:

– *isUsedBy* ⊆ *Library* × *Project*: a project includes a third-party library to make use of the library's functionalities. For the sake of presentation, in the rest of this paper, *library* and *dependency* are used interchangeably to indicate a third-party library;
– *develops* ⊆ *Developer* × *Class*: a developer contributes to the development of a class in a software project;
– *stars* ⊆ *User* × *Project*: it represents projects that a given user has starred. This relationship is only applicable to GitHub.

Figure 2 depicts an example of the graph representation for various OSS artifacts. There are several semantic edges to describe the mutual relationship between graph nodes. For example, the edge *includes* describes the relationship between a project and a third-party library, whereas the edge *hasSourceCode* dictates that a project contains a source code file. The graph structure facilitates similarity computation [7]. For instance, several existing algorithms are able to compute the similarity between *project#1* and *project#2* as they are indirectly connected by the pair of edges, i.e., *hasSourceCode* and *implements* [19],[39]. This semantic path reflects the actual relevance of the projects, they contain classes that implement a common interface. The similarity is further enforced by another path via *hasSourceCode* and *invokes*, leading to two API functions, i.e., *API#1* and *API#2*. The two projects are a bit more similar since they invoke same APIs. Analogously, the similarity between *project#1* and *project#3* can also be inferred since they both include two third-party libraries *lib#1* and *lib#2*, and projects share similar libraries are considered to be similar [32].

The graph structure allows for similarity computation on different artifacts. For instance, it is possible to compute similarities among developers: we see that developers *dev#1* and *dev#2* share a common activity, they develop two classes, i.e., *HttpSocket.java* and *FtpSocket.java* and these classes are somehow similar. In particular, both *HttpSocket.java* and *FtpSocket.java* implement *Socket.java*, furthermore, they all invoke *API#1* and *API#2* in their code.

To understand how to incorporate existing APIs into current code, a developer normally looks for API documentations that describe the constituent functions. For instance, StackOverflow provides the developer with a broader insight of API usage, and in some cases, with sound code examples [3],[43]. In Figure 2, there is a StackOverflow post, i.e., *Post#1* contains code snippets with two function calls *API#2* and *API#3*. In practice, this is a typical scenario when users discuss the usage of libraries containing *API#2* and *API#3*. In this respect, it might be helpful if we recommend *Post#1* to the developer of class *FtpSocket.java*. This is completely feasible since the graph structure allows one to compute the similarity between *Post#1* and *FtpSocket.java*. In the end, a recommendation engine can provide the developer with a list of StackOverflow posts that are relevant to the code being developed.

The graph structure allows for the integration of different relationships as depicted in Figure 2. CROSSSIM has been designed as a general framework to compute software similarity by exploiting both low-level and high-level features.

3.2   SimRank: Computing Graph Similarity

Graph similarity is an active field and receives a significant attention from the research community. Computing similarity among graph nodes has been applied to solve different problems in Computer Science. For instance, graph algorithms have been used to measure the similarities among social network nodes [34],[58], proteins [24], RDF graph nodes [13], to name a few.

In this paper, we apply graph similarity to solve the problem of computing the similarities among various OSS projects. First, we recall some notations as follows. A directed graph is defined as a tuple $G = (V, E, R)$, where V is the set of vertices, E is the set of edges, and R represents the relationship among the nodes. A graph consists of nodes and oriented links with semantic relationships [6]. A triple <*subject*, *predicate*, *object*> with (*subject*, *object* $\in$ V) and *predicate* $\in$ E states that node *subject* is connected to node *object* by means of the edge labelled with *predicate*. To evaluate the similarity of two nodes in a graph, their intrinsic characteristics like nodes, links, and their mutual interactions are incorporated into the similarity calculation [13]. Among others, feature-based semantic similarity metrics gauge the similarity between graph nodes as a measure of commonality and distinction of their hallmarks. By feature-based similarity, objects are represented as a set of common and distinctive features and the similarity between two objects is computed by comparing their features [54].

Many semantic similarity metrics first attempt to characterize resources in graphs representing sets of features and then perform similarity calculation on them. SimRank has been developed to calculate similarities based on mutual relationships between graph nodes [19]. Considering two nodes, the more similar nodes point to them, the more similar the two nodes are. We take an example in Figure 3 to illustrate how SimRank works in practice. There, node 1 is similar to node 2 since both are pointed by node 5. Comparably, node 3 is similar to node 4 as they are pointed by node 6. As a result, the two nodes α and β are highly similar because they are concurrently pointed by other four nodes in the graph, i.e., 1, 2, 3, and 4, considering that 1 and 2 as well as 2 and 3 are pairwise similar. In this sense, the similarity between α and β is computed by using a fixed-point function, taking into consideration the accumulative similarity by their pointing nodes. Given $k \geq 0$ we have $R^{(k)}(\alpha, \beta) = 1$ with $\alpha = \beta$ and $R^{(k)}(\alpha, \beta) = 0$ with $k = 0$ and $\alpha \neq \beta$, SimRank is computed as follows [19]:

$$R^{(k+1)}(\alpha, \beta) = \frac{\Delta}{|I(\alpha)| \cdot |I(\beta)|} \sum_{i=1}^{|I(\alpha)|} \sum_{j=1}^{|I(\beta)|} R^{(k)}(I_i(\alpha), I_j(\beta)) \qquad (5)$$

where Δ is a damping factor ($0 \leq \Delta < 1$); $I(\alpha)$ and $I(\beta)$ are the set of incoming neighbors of α and β, respectively. $|I(\alpha)| \cdot |I(\beta)|$ is the factor used to normalize the sum, thus forcing $R^{(k)}(\alpha, \beta) \in [0, 1]$.

By using the graph representation as in Section 3.1, we are able to transform the OSS ecosystem into a mathematically computable format. This graph structure allows for the application of various similarity algorithms. In CROSSSIM we adopt SimRank as the mechanism for computing similarities among OSS graph nodes. However, other similarity algorithms can also be flexibly integrated into CROSSSIM, as long as they are designed for graphs [41]. The utilization of SimRank is convenient and practical also
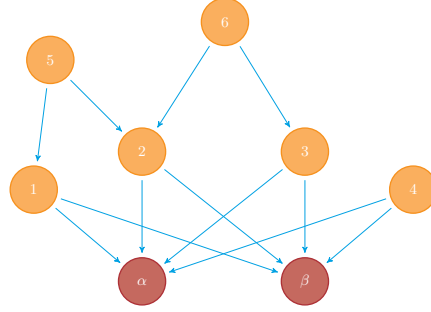
Fig. 3. An example of how SimRank works.

when various relationships are incorporated into the graph. Given the circumstances, the algorithm does not need to be changed since it only works on the basis of nodes and edges. In this sense, CROSSSIM is a versatile similarity tool as it can accept various input features regardless of their format.

To study the performance of CROSSSIM we conducted a comprehensive evaluation using a dataset collected from GitHub. To aim for an unbiased comparison, we opted for existing evaluation methodologies from other studies of the same type [30],[32],[60]. Together with other metrics typically used for evaluations, i.e., Success rate, Confidence, and Precision, we decided to use also Ranking to measure the sensitivity of the similarity tools to ranking results. The details of our evaluation are given in the next section.

4 Evaluation

In this section we describe the process that has been conceived and applied to evaluate the performance of CROSSSIM compared to some baselines. We opt for MUDABLUE, CLAN, and REPOPAL to compare with CROSSSIM. The rationale behind the selection of these approaches is that they are well-established algorithms and have demonstrated their effectiveness in various settings. According to *Zhang* et al. [60], by applying the same experiment settings and evaluating on the same dataset, the authors demonstrated that REPOPAL outperforms CLAN in terms of Confidence and Precision. Meanwhile, CLAN has a better performance than that of MUDABLUE, also with respect to *Confidence* and *Precision* [32]. Furthermore, REPOPAL works on GitHub Java repositories containing rich metadata that is suitable for building graph by CROSSSIM. Intuitively, we consider all these tools as a good starting point for a performance comparison. Furthermore, our evaluation aims at comparing two low-level similarity tools, i.e., MUD-ABLUE and CLAN with two high-level similarity ones, i.e., REPOPAL and CROSSSIM.

The evaluation process that has been applied is shown in Figure 4 and consists of activities and artifacts that are going to be explained later on this section. In particular, a set of Java projects (see Section 4.1) has been crawled to feed as input for the computation by all approaches, i.e., MUDABLUE, CLAN, REPOPAL, and CROSSSIM. Afterwards, a set of projects is selected as queries to compute similarities against all the remaining OSS projects. Once the scores have been computed, for each similarity tool,
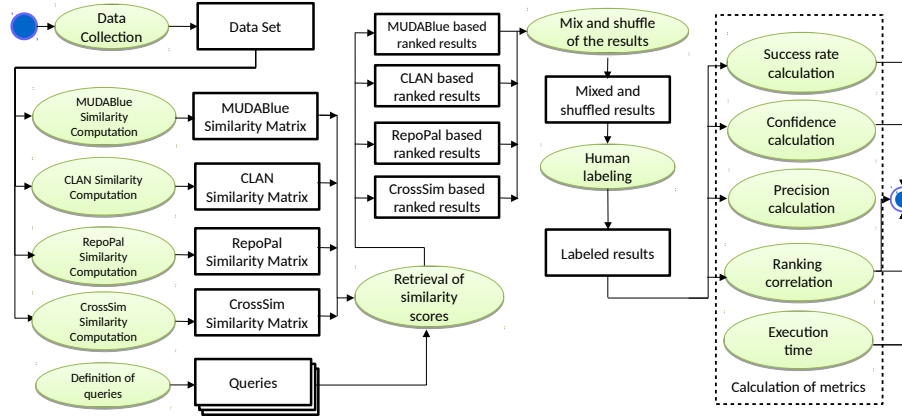
Fig. 4. Evaluation process.

some of the top similar projects are chosen, mixed with results by the other tools, and eventually evaluated by humans. The outcomes are then analyzed using various quality metrics.

Since the implementations of the baselines are no longer available for public use, we reimplemented MUDABLUE, CLAN, and REPOPAL by strictly following the descriptions in the original papers [15],[32],[60]. Such implementations, including the CROSSSIM one, are available online in GitHub [40] to facilitate future research.

4.1 Dataset

To compare the performance of CROSSSIM with those of the baselines, it is necessary to execute them on the same set of OSS projects. The collected dataset needs to be suitable as input for all four similarity engines. By MUDABLUE and CLAN, there are no specific requirements since both tools rely solely on source code to function. For REPOPAL and CROSSSIM, we can consider only projects that satisfy certain criteria. In particular, the collected projects have to meet the following requirements:

- Providing the specification of their dependencies by means of `code.xml` or `.grad-le` files[5];
- Including at least 9 dependencies – a project with no or little information about dependencies may adversely affect the performance of CROSSSIM;
- Having the `README.md` file available – this is needed to enable the application of RepoPal;
- Being starred by at least 20 users as required by REPOPAL to work.

Furthermore, we realized that the final outcomes of a similarity algorithm have to be validated by human beings, and in case the projects are irrelevant by their very nature,

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[5] The files `pom.xml` and with the extension `.gradle` are related to management of dependencies by means of Maven (https://maven.apache.org/) and Gradle (https://gradle.org/), respectively.

the perception given by human evaluators would also be *dissimilar* in the end. This is valueless for the evaluation of similarity. Thus, to facilitate the analysis, instead of crawling projects in a random manner, we first manually observed projects in some specific categories (e.g., PDF processors, JSON parsers, Object Relational Mapping projects, and Spring MVC related tools). Once a certain number of projects for each category had been obtained, we also started collecting randomly to get projects from various categories.

Using the GitHub API, we crawled projects to provide input for the evaluation. Though the number of projects that fulfill the requirements of a single approach is high, the number of projects that meet the requirements of all approaches is considerably lower. For example, a project contains both `pom.xml` and `README.md`, albeit having only 5 dependencies, does not meet the constraints and must be discarded. The scraping is time consuming as for each project, at least 6 queries must be sent to get the relevant data. As a matter of fact, GitHub already sets a rate limit for an ordinary account[6], with a total number of 5, 000 API calls per hour being allowed. And for the search operation, the rate is limited to 30 queries per minute. Due to these reasons, we ended up getting a dataset of 580 projects that are eligible for the evaluation. The dataset we collected is published together with all tools for public usage [40].

(a) Number of forks, commits, and pull requests

(b) Number of forks and stars, and issues
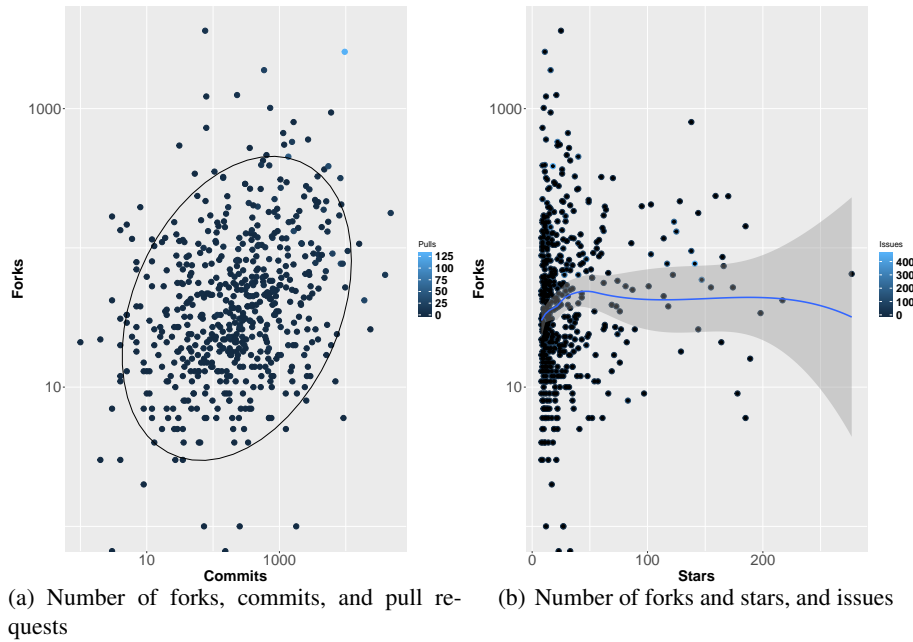
Fig. 5. The projects and their number of forks, commits, pull requests, stars, and issues.

Figure 5(a) and Figure 5(b) provide a summary on the projects and the number of forks, commits, stars, pull requests, and issues. The number of pull requests for most of the projects is considerably low, i.e., lower than 100; however their number of forks and commits is high. Forking is a means to contribute to the original repositories [20]. Furthermore, there is a strong correlation between forks and stars [8], as it is further witnessed in Fig. 5(b). A project with a high number of forks means that it can be considered as a sign of a well-maintained and well-received project. Similarly, as commits have a significant influence on the source code [4], the number of commits is also a good indicator of how a project has been developed.

Further than collecting projects for each category, we also started collecting random projects. These projects serve as a means to test the stability of the algorithms. If the algorithms work well, they will not perceive randomly added projects as similar to projects of some other specific categories. To this end, the categories and their corresponding cardinality to be studied in our evaluation are listed in Table 1. This is an approximate classification since a project might belong to more than one category.

No.	Name	# of Projects
1	SPARQL, RDF, Jena Apache	21
2	PDF Processor	8
3	Selenium Web Test	26
4	ORM	13
5	Spring MVC	51
6	Music Player	25
7	Boilerplate	38
8	Elastic Search	55
9	Hadoop, MapReduce	52
10	JSON	20
11	Miscellaneous Categories	271

Table 1. List of software categories.

As can be seen in Table 1, among 580 considered projects, 309 of them belong to some specific categories, such as SPARQL, RDF, Jena Apache, Selenium Test, Elastic Search, Spring MVC, etc. The other 271 projects being selected randomly belong to Miscellaneous Categories. These categories disperse in several domains and sometimes it happens that there is only one project in a category. For the sake of clarity, we do not introduce the full list of the categories in this paper.

4.2 Similarity Computation

To explain how the graph representation is exploited in CROSSSIM, Figure 6 sketches the sub-graph for representing the relationships between two projects AskNowQA/AutoSPARQL and AKSW/SPARQL2NL. The orange nodes are dependencies and their real names are depicted in Table 2. The turquoise nodes are developers who already starred the repositories. Every node is encoded using a unique number across the whole
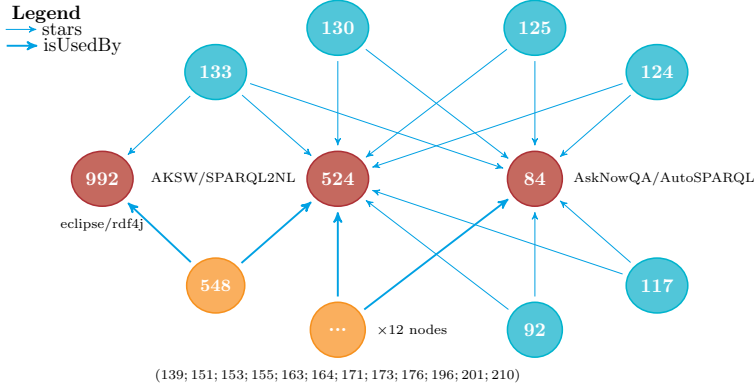
Fig. 6. Sub-graph showing a fragment of the representation for three projects, i.e., As-kNowQA/AutoSPARQL, AKSW/SPARQL2NL, and eclipse/rdf4j.

graph. To compute similarity between the two projects, SimRank is applied following Equation 5 and the damping factor Δ is empirically set to 0.85 according to some existing studies [19],[41]. The final result that lies between 0 and 1 is the similarity between two projects AskNowQA/AutoSPARQL and AKSW/SPARQL2NL.

ID	Name
139	org.apache.jena:jena-arq
151	org.dllearner:components-core
153	net.didion.jwnl:jwnl
155	net.sourceforge.owlapi:owlapi-distribution
163	net.sf.jopt-simple:jopt-simple
164	jaws:core
171	com.aliasi:lingpipe
173	org.dllearner:components-ext
176	org.apache.opennlp:opennlp-tools
196	org.apache.solr:solr-solrj
201	org.apache.commons:commons-lang3
210	javax.servlet:servlet-api
548	org.slf4j:log4j-over-slf4j

Table 2. Shared dependencies in Figure 6.

In the evaluation, we also investigate the effect of highly frequent libraries on the prediction performance. By analyzing the dataset in Section 4.1 and counting the number of all libraries, we obtained a ranked list of libraries, sorted according to the frequency of occurrence in the projects. Table 3 depicts the list of the six most frequent libraries in the dataset. For example, **junit:unit** is the most popular library and it is included by 447 projects. The second item on the list is **org.slf4j:slf4j-api** whose fre-

Dependency	Frequency
junit:junit	447
org.slf4j:slf4j-api	217
com.google.guava:guava	171
log4j:log4j	156
commons-io:commons-io	151
org.slf4j:slf4j-log4j12	129

Table 3. Most frequent dependencies in the considered dataset.

quency is much lower, it is found in 217 projects. The least popular one among the libraries in Table 3 is **org.slf4j:slf4j-log4j12**, and it appears in 129 projects.

Query definition Among 580 projects in the dataset, 50 have been selected as queries. We did not sample them randomly but selected those coming from some specific categories. This is due to the fact that the dataset is rather small and if we randomly selected queries which do not belong to any categories, we may end up retrieving irrelevant projects, and this is not useful for the validation process. We assume that the random selection can be done only when more projects available for training. To aim for variety, the queries have been chosen to cover different categories, e.g., SPARQL and RDF, Selenium Test, Elastic Search, Spring MVC, Hadoop, Music Player as listed in Table 4.

Retrieval of similarity scores Our evaluation has been conducted in line with some other existing studies [30],[32],[60]. In particular, for each query in the set of the 50 projects defined in the previous step, similarity is computed against all the remaining projects in the dataset using the SimRank algorithm discussed in Section 3.2. From the retrieved projects, only top 5 are selected for the subsequent evaluation steps. For every query, similarity is also computed using MUDABLUE, CLAN, and REPOPAL to get the top-5 most similar retrieved projects.
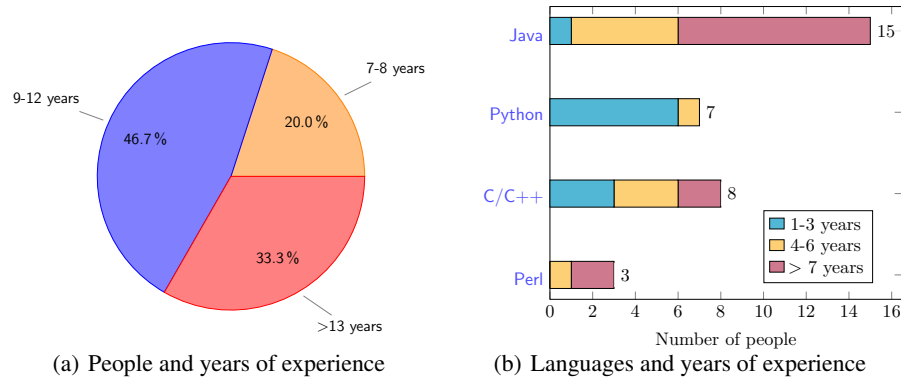
4.3 User Evaluation

For each similarity tool, the outcomes of the computation are a ranked list of similar projects. It is necessary to evaluate how relevant the projects are, compared to the query project. Since a user evaluation is the only way to evaluate the outcome [32],[60], we involved a group of 15 software developers to participate in the manual evaluation. Some of the participants are master students, and most of them work as software developers or researchers in academic and industry. Before the evaluation, we sent each evaluator a tutorial on how to conduct the scoring process. Furthermore, to get information about the participants related to their development background, we sent them a questionnaire similar to the one presented in [1],[32]. According to the survey, all the participants are capable of at least 2 different programming languages, and their favorite code platform is StackOverflow, where they normally search for posts that are useful for their current development tasks. In addition, most of them tend to re-use code fragments collected from external sources quite often.

No.	Project name	No.	Project name
1	neo4j-contrib/sparql-plugin	26	mariamhakobyan/elasticsearch-river-kafka
2	AskNowQA/AutoSPARQL	27	OpenTSDB/opentsdb-elasticsearch
3	AKSW/Sparqlify	28	codelibs/elasticsearch-cluster-runner
4	AKSW/SPARQL2NL	29	opendatasoft/elasticsearch-plugin-geoshape
5	pranab/beymani	30	huangchen007/elasticsearch-rest-command
6	sayems/java.webdriver	31	pitchpoint-solutions/sfs
7	psaravan/JamsMusicPlayer	32	javanna/elasticsearch-river-solr
8	webdriverextensions/webdriverextens-ions	33	mesos/hadoop
9	dadoonet/spring-elasticsearch	34	pentaho/big-data-plugin
10	seleniumQuery/seleniumQuery	35	asakusafw/asakusafw
11	bonigarcia/webdrivermanager	36	klarna/HiveRunner
12	selenium-cucumber/selenium-cucumber-java	37	sonalgoyal/hiho
13	conductor-framework/conductor	38	pyvandenbussche/sparqles
14	caelum/vraptor	39	lintool/Ivory
15	caelum/vraptor4	40	GoogleCloudPlatform/bigdata-interop
16	KEN-LJQ/WMS	41	Conductor/kangaroo
17	white-cat/jeeweb	42	datasalt/pangool
18	livrospringmvc/lojacasadocodigo	43	laserson/avro2parquet
19	spring-projects/spring-mvc-showcase	44	Knewton/KassandraMRHelper
20	sonian/elasticsearch-jetty	45	blackberry/KaBoom
21	testIT-WebTester/webtester-core	46	jt6211/hadoop-dns-mining
22	elastic/elasticsearch-metrics-reporter-java	47	xebia/Xebium
23	elastic/elasticsearch-support-diagnostics	48	TheAndroidMaster/Pasta-Music
24	SpringDataElasticsearchDevs/spring-data-elasticsearch	49	SubstanceMobile/GEM
25	javanna/elasticshell	50	markzhai/LyricHere

Table 4. List of queries for evaluation [40].

Figure 7(a) depicts the number of years that the developers have spent for software development activities. All the participants have at least 7 years of programming experience, two of them have more than 20 years. In Figure 7(b), we show the number of people and their corresponding number of years of programming experience for different languages. Among others, Java is the programming language that all developers are knowledgeable about, with at least two years of experience. Nine of the developers have spent more than 7 years working with Java. This is highly advantageous for our user evaluation since all projects included in the dataset introduced in Section 4.1 are written in Java, and we assume that skillful developers shall have a better judgment about the

(a) People and years of experience

(b) Languages and years of experience

Fig. 7. A summary of the participants' software development experience.

similarities among projects. The knowledge of different programming languages, i.e., Perl, Python, C/C++, is also a plus for the evaluation process.

By the user evaluation, in order to have a fair evaluation, for each query we mixed and shuffled the top-5 results generated from the computation by each similarity metric in a single Google form and presented them to the evaluators who then inspected and given a score to every pair. This mimics a *taste test* where users are asked to evaluate a product, e.g., food or drink, without having a priori knowledge about what is being addressed [16],[42]. This aims at eliminating any bias or prejudice against a specific similarity metric. In particular, given a query, a manual labeling process is performed to evaluate the similarity between the query and the corresponding retrieved projects. The participants are asked to label the similarity for each pair of projects (i.e., *<query, retrieved project>*) with regards to their application domains and functionalities using the scales listed in Table 5 [32].

Scale	Description	Score
Dissimilar	The functionalities of the retrieved project are completely different from those of the query project	1
Neutral	The query and the retrieved projects share a few functionalities in common	2
Similar	The two projects share a large number of tasks and functionalities in common	3
Highly similar	The two projects share many tasks and functionalities in common and can be considered the same	4

Table 5. Similarity scales.

For example, an OSS project p_1 that performs the sending of files across a TCP/IP network is somehow similar to an OSS project p_2 that exchanges text messages between two users, i.e., $Score(p_1, p_2) = 3$. However, an OSS project p_3 with the functionalities of a pure text editor is dissimilar to both p_1 and p_2, i.e., $Score(p_1, p_2) =$

$Score(p_1, p_3) = 1$. Given a query, a retrieved project is considered as a *false positive* if its similarity to the query is labeled as *Dissimilar* (1) or *Neutral* (2). In contrast, *true positives* are those retrieved projects that have a score of 3 or 4, i.e., *Similar* or *Highly similar*. A good similarity approach should produce as much true positives as possible.

To aim for a reliable comparison, we followed the same procedures utilized by related work. For overlapping pairs, i.e., those that appear in the ranked lists of two or more algorithms, we chose just one of them and presented it to one of the participants. This aims to avoid having one pair with different scores. Furthermore, the labeling results by a participant were then double-checked by another one to aim for soundness of the outcomes. By carefully investigating the results, we realized that in most cases, the evaluators agree on the evaluation scores. In case there is any disagreement about a final score between any two evaluators, a senior researcher is involved to inspect the pair again to reach a consensus.

4.4 Evaluation Metrics

To evaluate the outcomes of the algorithms with respect to the user evaluation, the following metrics have been considered as typically done in related work [30],[32],[60]:

- *Success rate*: if at least one of the top-5 retrieved projects is labelled *Similar* or *Highly similar*, the query is considered to be successful. *Success rate* is the ratio of successful queries to the total number of queries;
- *Confidence*: Given a pair of *<query, retrieved project>* the confidence of an evaluator is the score she assigns to the similarity between the projects;
- *Precision*: The precision for each query is the proportion of projects in the top-5 list that are labelled as *Similar* or *Highly similar* by humans.

Further than the previous metrics, we propose an additional one to measure the ranking produced by the similarity tools. For a query, a similarity tool is deemed to be good if all top-5 retrieved projects are relevant. In case there are false positives, i.e., those that are labeled *Dissimilar* and *Neutral*, it is expected that these will be ranked lower than the true positives. In case an irrelevant project has a higher rank than that of a relevant project, we suppose that the similarity tool is generating an improper recommendation. The *Ranking* metric presented below is a means to evaluate whether a similarity metric produces properly ranked recommendations.

- *Ranking*: The obtained human evaluation has been analyzed to check the correlations among the ranking calculated by the similarity tools and the scores given by the human evaluation. To this end the Spearman's rank correlation coefficient r_s [48] is used to measure how well a similarity metric ranks the retrieved projects given a query. Considering two ranked variables $r_1 = (\rho_1, \rho_2, .., \rho_n)$ and $r_2 = (\sigma_1, \sigma_2, .., \sigma_n)$, r_s is defined as: $r_s = 1 - \frac{6 \sum_{i=1}^{n} (\rho_i - \sigma_i)^2}{n(n^2-1)}$. Because of the large number of ties, we also used *Kendall's tau* [21] coefficient, which is used to measure the ordinal association between two considered quantities. Both r_s and τ range from -1 (perfect negative correlation) to +1 (perfect positive correlation); $r_s = 0$ or $\tau = 0$ implies that the two variables are not correlated.

Finally, we consider also the *execution time* related to the application of the four approaches on the dataset to obtain the corresponding similarity matrices.

4.5 Research Questions

To study the performance of the considered tools in detecting similar projects for the set of queries, the following research questions are considered:

- *RQ_1: Which graph configuration brings the best performance to* CROSSSIM*?* Our proposed approach allows for a flexible computation by incorporating different features in a graph. We investigate which types of edges sustain similarity computation by considering different test configurations. In this way, we identify the configuration that fosters the best prediction outcome for CROSSSIM.
- *RQ_2: Which similarity approach between* MUDABLUE, CLAN, REPOPAL, *and* CROSSSIM *yields a better performance in terms of Success rate, Confidence, Precision, and Ranking?* By this question, we compare the performance of the approaches concerning the ability to produce accurate recommendations. In the context of software development, providing relevant results is of highly importance since a developer would expect a set of similar projects to the project being developed.
- *RQ_3: Which similarity approach is more efficient with respect to execution time?* An important factor for a similarity tool is the ability to compute within an acceptable amount of time. This research question aims at measuring the time needed for a tool to produce a final recommendation.

5 Experimental Results

In Section 5.1, the data that has been obtained as discussed in the previous section is analyzed to answer the research questions, i.e., **RQ_1**, **RQ_2**, and **RQ_3**. Afterwards, Section 5.2 presents discussions related to the experimental outcomes. Finally, threats to the validity of the evaluation are also discussed in Section 5.3.

5.1 Data Analysis

RQ_1: Which graph configuration brings the best performance to CROSSSIM*?*
  We investigate the implication of graph structure on the outcome of CROSSSIM by considering various types of edges. This aims at identifying the set of features that contribute to the performance gain. First, only star events are used to build the graph with the *stars* edges (see Fig. 2), and this configuration is called CROSSSIM$_1$. Correspondingly, in CROSSSIM$_2$ the graph is built with only the *isUsedBy* edges by using only dependencies. By CROSSSIM$_3$ we consider both the relationships *stars* and *isUsedBy* together to compute similarity. Afterwards, we extend CROSSSIM$_3$ by incorporating also committers, i.e., the *develops* relationship, and this yields configuration CROSSSIM$_4$. Similarly, with CROSSSIM$_5$ we investigate the effect of frequent dependencies by adding them to CROSSSIM$_3$. Finally, we take into account all the above mentioned

Configuration	stars	isUsedBy	develops	Fre. deps.
CROSSSIM_1	✓	✗	✗	✗
CROSSSIM_2	✗	✓	✗	✗
CROSSSIM_3	✓	✓	✗	✗
CROSSSIM_4	✓	✓	✓	✗
CROSSSIM_5	✓	✓	✗	✓
CROSSSIM_6	✓	✓	✓	✓

Table 6. CROSSSIM test configurations.

edges, resulting in CROSSSIM_6. Table 6 gives a detailed description of the test configurations used to internally compare CROSSSIM.

Since the manual evaluation is a time consuming process, we decided to exploit only a subset of the queries to address this research question. In particular, we selected the first 20 queries in Table 4, i.e., from number 1 to 20 and provided as input for CROSSSIM and the results are depicted in Table 7.

Among the configurations, CROSSSIM_2 gains the lowest prediction performance. In particular, it gets 0.90 as success rate and 0.51 as precision. This implies that using only dependencies as features does not contribute to a good performance. Compared to CROSSSIM_2, CROSSSIM_1 has a slightly better performance as its success rate and precision are 0.95 and 0.61, respectively. By referring back to the REPOPAL approach (see Section 2), where information related to the star event such as stargazers and star time gap is used to compute similarity, we come to the conclusion that stars are useful for the detection of similar GitHub repositories. However, we assume that more investigations are needed to understand better the effect of stars on similarity computation. This issue remains as a future work.

	CROSSSIM_1	CROSSSIM_2	CROSSSIM_3	CROSSSIM_4	CROSSSIM_5	CROSSSIM_6
Success rate (%)	**95**	**90**	**100**	**100**	**100**	**100**
Precision	0.62	0.51	**0.80**	0.76	0.75	0.70

Table 7. Comparison of different CROSSSIM configurations.

We consider CROSSSIM_5 in combination with CROSSSIM_6 to observe the effect of the adoption of committers. According to Table 7, CROSSSIM_5 gains a success rate of 100%, with a precision of 0.75. The number of false positives by CROSSSIM_6 goes up, thereby worsening the overall performance considerably with 0.70 being as the precision. The performance degradation is further witnessed by considering CROSSSIM_3 and CROSSSIM_4 together. Both get 100% as success rate, however CROSSSIM_3 obtains a better precision, i.e., 0.80 compared to 0.76 by CROSSSIM_4. We come to the conclusion that the inclusion of all developers who have committed updates at least once to a project in the graph is counterproductive as it adds a decline in precision. In this sense, we make an assumption that the deployment of a weighting scheme for developers may help counteract the degradation in performance.

Next, CROSSSIM_3 and CROSSSIM_5 are considered together to analyze the effect of the removal of the most frequent dependencies. CROSSSIM_3 outperforms CROSS-

SIM_5 as it gains a precision of 0.80, the highest value among all, compared to 0.75 by CROSSSIM$_5$. The removal of the most frequent dependencies helps also improve the performance of CROSSSIM$_4$ in comparison to CROSSSIM$_6$. Together, this implies that the elimination of too popular dependencies in the original graph is a profitable amendment. This is understandable once we get a deeper insight into the design of SimRank presented in Section 3.2. There, two projects are deemed to be similar if they share a same dependency, or in other words their corresponding nodes in the graph are pointed by a common node. However, with frequent dependencies as in Table 3 this characteristic may not hold anymore. For example, two projects are pointed by junit:junit because they use JUnit[7] for testing. Since testing is a common functionality of many software projects, it does not help contribute towards the characterization of a project and thus, needs to be removed from the considered graph.

Among the considered experimental configurations, CROSSSIM$_3$, where star events and dependencies are used together to build the graph, obtains the best prediction performance. The graph structure considerably affects the outcome of the similarity computation. In this sense, finding a graph structure that facilitates similarity computation is of paramount importance.


RQ$_2$: Which similarity approach between MUDABLUE, CLAN, REPOPAL, *and* CROSSSIM *yields a better performance in terms of Success rate, Confidence, Precision, and Ranking?* For this research question, we compared the best configuration CROSSSIM$_3$ with the baselines. The experimental results are shown in Table 8 and Figure 8. In particular, Table 8 depicts Success rate, Precision, Execution time, Spearman's (r_s), and Kendall's tau (τ) for all similarity tools. The obtained results demonstrate that REPOPAL is a good choice for computing similarity among OSS projects. Its success rate and precision are superior to those of MUDABLUE and CLAN. Both MUDABLUE and CLAN obtain a success rate of 60%, however REPOPAL gets a success rate of 100%. Furthermore, the precision of MUDABLUE and CLAN is 0.22 which is considerably lower than 0.71, the corresponding value for REPOPAL.

	MUDABLUE	CLAN	REPOPAL	CROSSSIM$_3$
Success rate (%)	60	60	**100**	**100**
Precision	0.22	0.22	0.71	**0.78**
Execution time (min)	380	22	240	**12**
Spearman's (r_s)	-0.01	-0.08	-0.132	**-0.230**
Kendall's tau (τ)	-0.01	-0.07	-0.108	**-0.214**

Table 8. Comparison of the similarity approaches.

In comparison with the other tools, CROSSSIM$_3$ has a better performance concerning Success rate and Precision. Both REPOPAL and CROSSSIM$_3$ gain a Success rate of 100%. However, CROSSSIM$_3$ gets 0.78 as precision which is higher than 0.71, the

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[7] JUnit: `http://junit.org/junit5/`
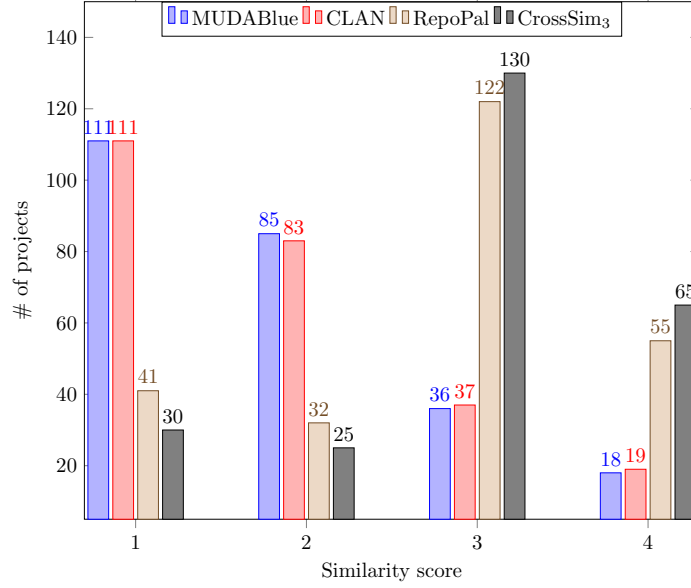
Fig. 8. Confidence.

corresponding value by REPOPAL. In this sense, CROSSSIM outperforms the baselines with respect to success rate and precision.

The Confidence for the similarity tools is shown in Figure 8. MUDABLUE has more false negatives than CLAN does, i.e., pairs that are scored with 1 or 2. In particular, the number of project pairs that have been assigned the score of 1 is 111 for both MUDABLUE and CLAN. Meanwhile, the corresponding number of pairs that have the score of 2 is 85 and 83 for MUDABLUE and CLAN, respectively. In addition, CLAN has more true positives, i.e., scores of either 3 or 4. In this sense, we conclude that CLAN has a slightly better performance in comparison to MUDABLUE.

By this index, i.e., Confidence, CROSSSIM$_3$ yields a better outcome as it has more scores that are either 3 or 4 and less scores that are 1 or 2. For the similarity score of 3, CROSSSIM$_3$ finds 130 relevant projects, whereas REPOPAL returns 122 projects. The same trend can also be witnessed for the similarity score of 4: the number of projects that REPOPAL and CROSSSIM$_3$ retrieve is 55 and 65, respectively. It is evident that CROSSSIM$_3$ achieves a better Confidence compared to that of REPOPAL.

In addition to the conventional quality indexes, we investigated the ranking produced by the metrics using the Spearman's (r_s) and Kendall's tau (τ) correlation indexes. The aim is to see how good is the correlation between the rank generated by each metric and the scores given by the developers, which are already sorted in descending order. In this way, a lower r_s (τ) means a better ranking. Both indexes r_s and τ are computed for all 50 queries and related first five results. The value of r_s is -0.230 for CROSSSIM$_3$ and -0.132 for REPOPAL. The value of τ is -0.214 for CROSSSIM$_3$ and -0.108 for REPOPAL. By this quality index, CROSSSIM$_3$ performs slightly better

than REPOPAL. Compared to MUDABLUE, CLAN obtains a superior ranking with respect to both r_s and τ. In particular, CLAN obtains -0.08 and -0.07 for r_s and τ, respectively; and MUDABLUE gets -0.01 for both r_s and τ.

The experimental results confirm the claim made by the authors of REPOPAL [60]: The system obtains a better recommendation performance than CLAN in terms of Success rate, Precision and Confidence. Furthermore, the ranking by REPOPAL is also better to those of MUDABLUE and CLAN.

> Compared to MUDABLUE, CLAN, and REPOPAL, CROSSSIM gains a better performance in terms of Success rate, Precision, Confidence, and Ranking. The obtained results confirm our hypothesis that the incorporation of various features, e.g., dependencies and star events into graph facilitates similarity computation. Furthermore, CROSSSIM is more flexible as it can include other artifacts in similarity computation without affecting the internal design.

RQ$_3$: Which similarity approach is more efficient with respect to execution time? We measure the time needed to produce recommendations for all the four similarity approaches. The execution time related to the application of the analyzed techniques is shown in the third row of Table 8. For the experiments, a laptop with Intel Core i5-7200U CPU @ 2.50GHz $\times$ 4, 8GB RAM, Ubuntu 16.04 was used. In such a configuration, REPOPAL takes $\approx$4 hours to generate the similarity matrix, whereas the execution of CROSSSIM$_3$, including both the time for generating the input graph and that for generating the similarity matrix, takes $\approx$12 minutes. Such an important time difference is due to the time needed to calculate the similarity between README.md files, on which REPOPAL relies. MUDABLUE takes 380 minutes to complete the computation, even though most of the time (310 minutes) is devoted to the creation of the internal matrices needed to perform the similarity calculation. Meanwhile, CLAN needs only 22 minutes to do the complete computation. Also in this case the creation of the internal structures is the most computational demanding phase, it takes 21 minutes. Such execution times make evident the distinction between high-level and low-level similarity approaches. In particular, MUDABLUE takes into consideration all source code artifacts for computation, such as variable names, method names, the matrix used to represent the input may become huge. CLAN considers only API calls for computation. This is the reason why the computation times for MUDABLUE and CLAN are much higher than those of REPOPAL and CROSSSIM that instead consider just project metadata.

> CROSSSIM is the most efficient tool as it generates the similarity matrix in a short time as shown in Table 8.

5.2 Discussions

To aim for a reliable evaluation, the experiments in this paper have been performed in line with existing studies [32],[60]. As can be seen, CROSSSIM has a better performance than that of MUDABLUE, CLAN, and REPOPAL with respect to different quality indicators. The gain in CROSSSIM's performance demonstrates that the consideration of different artifacts, e.g., projects, libraries in a mutual relationship, instead

of individual items brings a substantial benefit. Referring back to the REPOPAL paper [60], we see that the success rate of REPOPAL in our evaluation is considerably higher than that in the original experiments. This can be explained as follows: According to our investigation on the dataset considered by REPOPAL[8], the chosen projects scatter in several categories and the number of projects belonging to certain categories is rather low. That means, the similarities among the projects are low by their origin. However, in our dataset, projects have been deliberately selected so as to converge on some specific categories, thus increasing their mutual similarities. This makes the possibility that a query gets a relevant project which comes from the same category become superior to that by the original REPOPAL dataset. As a result, the success rate in our experiments increases considerably.

In our evaluation, compared to MUDABLUE, CLAN gains a better confidence: it returns fewer false negatives and more true positives. This partly confirms the findings by McMillan *et al.* in their work [32]. However, both MUDABLUE and CLAN obtain comparable success rate and precision. This is not completely consistent with their claim since they demonstrated that CLAN gained a better performance compared to that of MUDABLUE. Our intuition is that the discrepancy between our work and that of McMillan *et al.* [32] may attribute to following reasons: *(i)* although we attempted to strictly follow descriptions by the related papers to implement the tools, the final implementations might not be exactly identical to the original ones. Particularly, the selection of various parameters for the LSA implementation used in MUDABLUE and CLAN may considerably contribute towards the difference; *(ii)* the dataset in our evaluation is different from the one used for evaluating CLAN. Altogether, this should introduce some fluctuations in the performance of both approaches.

Currently, CROSSSIM supports the incorporation of *isUsedBy*, *develops*, and *stars* to compute similarities [40], and thus being a high-level similarity metric. However, it is feasible to consider also low-level features, such as package names, class names, or API function calls as partly shown in Figure 1. In a recent work [37],[38], we exploited CROSSSIM to compute similarities by considering low-level information, i.e., API function calls as features. In this way, CROSSSIM becomes a *hybrid* similarity metric as it deals with both metadata (high-level) and source code (low-level). Furthermore, since CROSSSIM allows for the integration of various graph algorithms for calculating similarity, the deployment of different techniques rather than SimRank might possibly improve the overall recommendation performance, depending on the set of features. To this end, the selection of a proper similarity technique for each type of graphs can be considered as an open research topic.

We assume that the graph structure may have a dramatic influence on its performance. Thus, finding a suitable graph that facilitates the computation is an interesting research topic and needs further investigations. Moreover, since very frequent nodes are not useful for similarity computation, it is necessary to define a threshold at which a node is considered to be frequent.

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[8] `https://github.com/yunzhang28/RepoPal/blob/master/1000repo.xlsx`

5.3 Threats to Validity

In this section, we investigate the threats that may affect the validity of the experiments as well as how we have tried to minimize them. In particular, we focus on the following threats to validity as discussed below.

Internal validity concerns any confounding factor that could influence our results. We attempted to avoid any bias in the evaluation and assessment phases: (*i*) by involving 15 developers with decent programming experience in the user evaluation. In particular, the results labeled by a participant were then double-checked by another one. In case there is a disagreement between any two evaluators, one more researcher was asked to investigate the pair again to reach a final decision; (*ii*) by completely automating the evaluation of the defined metrics without any manual intervention. Indeed, the implemented tools could be defective. To contrast and mitigate this threat, we strictly followed the descriptions in the original papers to re-implement the tools. Furthermore, we have run several manual assessments and counter-checks to validate the evaluation outcomes.

External validity refers to the generalizability of obtained results and findings. Concerning the generalizability of our approach, we were able to consider a dataset of 580 projects, due to the fact that the number of projects that meet the requirements of all the tools is low and thus required a prolonged scraping. During the data collection, we crawled both projects in some specific categories as well as random projects. The random projects served as a means to test the generalizability of our algorithm. If the algorithm works well, it will not perceive newly added random projects as similar to projects of the specific categories.

Construct validity is related to the experimental settings used to evaluate the similarity approaches. We addressed the issue seriously and attempted to simulate a real deployment scenario where the tools are used to search for similar GitHub repositories. In this way, we were able to investigate if the tools are really applicable to authentic usage.

Conclusion validity is whether the exploited experiment methodology is intrinsically related to the obtained outcome, or there are also other factors that have an impact on it. The evaluation metrics, i.e., Success rate, Confidence, Precision, Ranking, and Execution time might cause a threat to conclusion validity. To confront the issue, we employed the same metrics for evaluating all the similarity approaches.

6 Related Work

In this section, we review some of the most notable approaches that have been developed to measure the similarity between software systems or OSS projects. These approaches deal with the detection of: *(i)* similar open source applications, *(ii)* similar mobile applications, *(iii)* software plagiarisms and clones, and *(iv)* relevant third-party libraries.

To detect clone among Android apps, Wang *et al.* propose WuKong [57] which employs a two-phase process as follows. The first phase exploits the frequency of Android API calls to filter out external libraries. Afterwards, a fine-grained phase is performed

to compare more features on the set of apps coming from the first phase. For each variable, its feature vector is formed by counting the number of occurrences of variables in different contexts (Counting Environments - CE). An m-dimensional Characteristic Vector (CV) is generated using m CEs, where the i-th dimension of the CV is the number of occurrences of the variable in the i-th CE. For each code segment, CVs for all variables are computed. A code segment is represented by an $n \times m$ Characteristic Matrix (CM). For each app, all code segments are modelled using CM, yielding a series of CMs and they are considered as the features for the app. The similarity between two apps is computed as the proportion of similar code segments. The similarity between two variables v_1 and v_2 is computed using cosine similarity [53],[54] between their feature vectors. Evaluations on more than $100,000$ Android apps collected from 5 Chinese app markets show that the approach can effectively detect cloned apps [57]. CROSSSIM is also able to deal with low-level features as by WuKong if such features are integrated into the graph presented in Section 3.

Lo *et al.* develop TagSim[9], a tool that leverages tags to characterize applications and then to compute similarity between them [30]. Tags are terms that are used to highlight the most important characteristics of software systems [59] and therefore, they help users narrow down the search scope. TagSim can be used to detect similar applications written in different languages. Based on the assumption that tags capture better the intrinsic features of applications compared to textual descriptions, TagSim extracts tags attached to an application and computes their weights. This information forms the features of a given software system and can be used to distinguish it from others. The technique also differentiates between important tags and unimportant ones based on their frequency of appearance in the analyzed software systems. The more popular a tag across the applications is, the less important it is and vice versa. Each application is characterized by a feature vector, and each entry corresponds to the weight of a tag the application has. Eventually, the similarity between two applications is computed as the cosine similarity [53],[54] between the two vectors. To evaluate TagSim, more than a hundred thousands of projects have been collected and analyzed [30]. A total of 20 queries were used to study the performance of the algorithm in comparison with CLAN. The experimental results show that TagSim helps achieve better performance in comparison to CLAN.

Being inspired by CLAN, Linares-Vásquez *et al.* develop CLANdroid for detecting similar Android applications with the assumption that similar apps share some semantic anchors [28]. Nevertheless, in contrast to CLAN, CLANdroid works also when source code is not available as it exploits other high-level information. By extending the scope of semantic anchors for Android apps, starting from APK (Android Package) CLANdroid extracts quintuple features, i.e., identifiers, intents from source code, API calls and sensors from JAR files, and user permissions from the *AndroidManifest.xml*[10] specification. This file is a mandatory component for any Android app and it contains important information about it. For each feature, a feature-application matrix is built,

resulting in five different matrices. Latent Semantic Indexing is applied to all the matrices to reduce the dimensionality. Afterwards, similarity between a pair of applications is computed as the cosine similarity between their corresponding feature vectors from the matrix. Users can query for similar apps with a given app by specifying which feature is taken into consideration. Evaluations have been performed to study which semantic anchors are more effective [28]. The authors also analyze the impact of third-party libraries and obfuscated code when detecting similar apps, since these two factors have been shown to have significant impact on reuse in Android apps and experiments using APKs. The evaluation on a dataset shows that computing similarity based on API helps produce higher recall. According to the experimental results, the feature sensor is ineffective in computing similarity. By comparing with a ground-truth dataset collecting from Google Play, the study gives some hints on the mechanism behind the way Google Play recommends similar apps. CROSSSIM is relevant to CLANdroid since it can work with low-level features by representing function calls, API calls in the graph as we already demonstrated in our recent work [37],[38].

With the aim of finding apps with similar semantic requirements, SimApp has been developed to exploit high-level metadata collected from apps markets [9]. If two apps implement related semantic requirements then they are seen as similar. Each mobile application is modeled by a set of features, so called modalities. The following features are incorporated into similarity computation: *Name*, *Category*, *Developer*, *Description*, *Update*, *Permissions*, *Images*, *Content rating*, *Size* and *Reviews*. For each of these features, a function is derived for each of the features to calculate the similarity between applications. The final similarity score for a pair of apps is a linear combination of the multiple kernels with weights. Through the use of a set of training data, the optimal weights are determined by means of online learning techniques.

AnDarwin is an approach that applies Program Dependence Graphs to represent apps [12], and feature vectors are then clustered to find similar apps. Locality Sensitive Hashing [3] is used to find approximate near-neighbors from a large number of vectors. AnDarwin works according to the following stages: *(i)* It represents each app as a set of vectors computed over the app's Program Dependence Graphs; *(ii)* Similar code segments are found by clustering all the vectors of all apps; *(iii)* It eliminates library code based on the frequency of the clusters; *(iv)* Finally, it detects apps that are similar, considering both full and partial app similarity. AnDarwin has been applied to find similar apps by different developers (cloned apps) and groups of apps by the same developer with high code reuse (rebranded apps). An evaluation using more than $200,000$ apps from different Android markets demonstrated that the system can effectively detect cloned apps. LibRec is a tool that assists developers in leveraging existing libraries [51]. It suggests the inclusion of libraries that may be useful for a given project using a combination of rule mining and collaborative filtering techniques. *Association rule* mining is applied to find similar libraries that co-exist in many projects to extract libraries that are commonly used together. The component then rates each of the libraries based on their likelihood to appear together with the currently used libraries. A *collaborative filtering* technique is applied to search for top most similar projects and recommends libraries used by these projects. The libraries included by these projects are used as recommendations based on a score computed according to their popularity.

	Source code				Metadata					Descriptions
	MUDABlue [15]	CLAN [32]	CLANdroid [28]	WuKong [57]	SimApp [9]	AnDarwin [12]	TagSim [30]	LibRec [51]	RepoPal [60]	
Considered features										**Descriptions**
Dependencies	–	–	–	✓	–	–	–	✓	–	Set of third-party libraries that a project includes
API Calls	✓	✓	✓	✓	–	✓	–	–	–	API function calls that appear in the source code of the analyzed projects. They are used to build term-document matrices and then to calculate similarities among applications
Functions	✓	–	–	–	–	✓	–	–	–	Functions defined in a project's source code
Stars	–	–	–	–	–	–	–	–	✓	The GitHub star events occurred for each analyzed projects
Timestamps	–	–	–	–	–	–	–	–	✓	The point of time when a user stars a repository
Statements	✓	–	–	–	–	–	–	–	–	Source code statements
Identifiers	✓	–	✓	✓	–	–	–	–	–	All artifacts related to source code, such as variable names, function names, package names, etc.
App name	–	–	–	–	✓	–	–	–	–	Name of a mobile app may reveal its functionalities
Descriptions	–	–	–	–	✓	–	–	–	–	The description text of an app
Developers	–	–	–	–	✓	–	–	–	–	All developers who contribute to the development of a software/an app
Readme	–	–	–	–	✓	–	✓	–	–	Descriptions or *README.MD* files, used to describe the functionalities of an open source project
Tags	–	–	–	–	–	–	✓	–	–	The tags that are used by OSS platforms, e.g. SourceForge to classify and characterize an OSS project
Updates	–	–	–	–	✓	–	–	–	–	The newest changes made to the considered applications
Permissons	–	–	✓	–	✓	–	–	–	–	This feature is available by mobile apps. It specifies the permission of an app to handle data in a smartphone
Screenshots	–	–	–	–	✓	–	–	–	–	This feature is available by mobile apps. It is a picture representing an app
Contents	–	–	–	–	✓	–	–	–	–	Each app has content rating to describe its content and age appropriateness
Size	–	–	–	–	✓	–	–	–	–	Some similarity metrics assume that two apps whose size is considerably different cannot be similar
Reviews	–	–	–	–	✓	–	–	–	–	All user reviews for an app are combined in a document
Intents	–	–	✓	–	–	–	–	–	–	For a mobile app, an intent is description for an operation to be performed
Sensors	–	–	✓	–	–	–	–	–	–	In mobile devices, sensors can provide raw data to monitor 3-D device movement or positioning, or changes in the environment. A set of features can be built from sensors to characterize an app
Used techniques										
TDM & LSA	✓	✓	✓	–	–	–	–	–	–	TDM [10] and LSA [25] are generally used in combination to model the relationships between API calls/identifiers and software systems and to compute the similarities between them
COS	✓	✓	✓	✓	✓	–	✓	✓	✓	Cosine similarity [53],[54] is widely used in several algorithms for computing similarities among vectors
JCS	–	–	–	–	–	✓	–	–	✓	Jaccard index [18] is used for computing similarity between two sets of elements

Table 9. Summary of the similarity algorithms and their features.

Considering a set of projects and a set of libraries each project is characterized by a feature vector using the set of libraries it includes. The similarity between two projects is the cosine similarity between their feature vectors. In a previous work [36], we introduced CrossRec, a recommender system for providing software developers with third-party libraries. In this setting, CROSSSIM performs its computation using third-party libraries as the input features. By considering LibRec as baseline, we demonstrated that CrossRec obtains a superior performance with respect to various quality metrics.

A summary of all the similarity metrics introduced in Section 2 and Section 6 is depicted in Table 9. Most low-level similarity algorithms attempt to represent source code (and API calls) in a term-document matrix and then apply SVD to reduce dimensionality. The similarity is then computed as the cosine similarity between feature vectors. Among others, MUDABLUE, CLAN, and CLANdroid belong to this category. In contrast, high-level similarity techniques do not consider source code for similarity computation. They characterize software by exploiting available features such as descriptions, user reviews, and *README.MD* file. The similarity is computed as the cosine similarity of the corresponding feature vectors. For computing similarity between mobile applications, other specific features such as images and permissions are also incorporated. A current trend in these techniques is to exploit textual content to compute similarity, e.g., in AppRec [5], SimApp [9], TagSim [30].

A main drawback with this approach is that, same words can be used to explain different requirements or the other way around, the same requirements can be described using different words [15]. So it might be the case that two textual contents with different vocabularies still have a similar description or two files with similar vocabularies contain different descriptions. The matching of words in the descriptions as well as source code to compute similarity is considered to be ineffective as already stated in [32]. To overcome this problem, the application of a synonym dictionary like WordNet [33] is beneficial. Nevertheless, there is an issue with the approaches like REPOPAL where readme files are used for similarity computation. Since in general the descriptions for software projects are written in different languages, the comparison of readme files in different languages should yield dissimilarity, even though two projects may be similar. SimApp [9] is the only technique that attempts to combine several high-level information into similarity computation. It eventually applies a machine learning algorithm to learn optimal weights. The approach is promising, nevertheless it is only applicable in the presence of a decent training dataset, which is hard to come by in practice.

7 Conclusions

In this paper, we presented CROSSSIM, a framework for computing similarities among OSS projects. Through a review on some of the most notable methods for detecting similarity in software applications and open source projects, we came to the conclusion that a representation model that flexibly incorporates various features and semantic relationships is highly beneficial to similarity computation in the context of an OSS ecosystem. We considered the community of developers together with OSS projects, libraries as well as various artifacts and their mutual interactions as whole by using the graph

representation. In the graph, either humans or non-human factors have mutual dependency and implication on the others. By means of a graph, we are able to transform the relationships among various artifacts, e.g., developers, API utilizations, source code, interactions, into a mathematically computable format. The implementation of CROSS-SIM exploits SimRank to compute similarity in graphs and it can handle the following relationships: *isUsedBy*, *develops*, and *stars*. CROSSSIM is a versatile similarity tool as it can accept various input features regardless of their format.

We conducted an evaluation of computing similarities among OSS projects on a dataset of 580 GitHub Java projects. Using MUDABLUE, CLAN, REPOPAL as baselines, we studied the performance of our approach. The obtained results are promising, among the test configurations, CROSSSIM$_3$ has the best performance, where dependencies and star events are considered as features for the similarity computation. It is our belief that CROSSSIM is a good candidate for computing similarities among OSS projects. In order to enable the reproducibility of the performed experiments, we made available the source code implementation of MUDABlue, CLAN, REPOPAL, and CROSSSIM as also the dataset exploited and the corresponding user evaluation in our GitHub repository [40]. For future work, we are going to investigate in more detail the influence of graph structure on similarity computation. In addition, we plan to incorporate also low-level similarity features such as API function calls, package names, etc., into the graph to see if the recommendation performance can be improved. Last but not least, we are going to exploit CROSSSIM to automatically cluster OSS projects.

8   Acknowledgments

Appendix

Questionnaire

This is the questionnaire sent to the developers who took part in our user evaluation. We adopted most of the content proposed by McMillan *et al.* [1],[32]

1. How many years of programming experience do you have?
2. Which programming languages are you capable of? And how many years have you worked with them?

Language	Number of years
Java	
Python	
Perl	
C++/C#	
Others	

3. How often do you use code search engines?
4. What code search engines have you used and for how long?
5. How often do you reuse source code snippets collected from the search engines in your work?
6. According to your experience, what is the main obstacle to using code search engines?

Materials

We uploaded the materials created from the user evaluation in GitHub for future reference.[11]

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