SimAndro-Plus: On Computing Similarity of Android Applications

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Abstract. In this paper, we propose SimAndro-Plus as an improved variant of the state-of-the-art method, SimAndro, to compute the similarity of Android applications (apps) regarding their functionalities. SimAndro-Plus has two major differences with SimAndro: 1) it exploits two beneficial features to similarity computation, which are totally disregarded by SimAndro; 2) to compute the similarity score of an app-pair based on strings and package name features, SimAndro-Plus considers not only those terms co-appearing in both apps but also considers those terms appearing in one app while missing in the other one. The results of our extensive experiments with three real-world datasets and a dataset constructed by human experts demonstrate that 1) each of the two aforementioned differences is really effective to achieve better accuracy and 2) SimAndro-Plus outperforms SimAndro in similarity computation by 14% in average.

Keywords: android applications, apps data mining, feature extraction, API calls, manifest information, similarity computation

1. Introduction

Android applications (in short, apps) are rapidly growing in the number and variety \cite{5} \cite{17} distributed via the official Google Play Store\textsuperscript{3} and other third-party stores such as Amazon App Store\textsuperscript{4} and APKPure\textsuperscript{5}. Google Play Store contains a huge number of apps divided into various categories such as game, communication, and business \cite{11} \cite{24}. As the number of apps in app stores increases dramatically, even if they are divided into various categories, smartphone users face a serious problem to find relevant apps providing their required functionalities \cite{5} \cite{13}. Therefore, there is an important demand for app search engines or recommender systems to alleviate this problem where employing an accurate similarity method is one of the most challenging issues \cite{13} \cite{15}.

In the literature, some methods have been proposed for similarity computation of apps where we aim to find similar apps regarding their functionalities \cite{4} \cite{7} \cite{13} \cite{22}. To do

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this, proposed methods in references [4], [6], [22], SimApp [5], and DNADroid [7] extract the required features from the app stores; these feature might be inaccurate, varied in different app stores, unavailable, affected by language barrier, and unappropriated for similarity computation. Therefore, exploiting these features may lead us to inaccurate similarity computation [13]. On the contrary, SimAndro [13], an effective state-of-the-art method, exploits the features extracted (i.e., mined) from apps and the Android platform itself to compute the similarity of apps. The motivation behind SimAndro is that apps contain helpful and unique features for similarity computation such as API calls and manifest information that clearly capture the apps functionalities.

In this paper, we propose SimAndro-Plus as an improved variant of SimAndro to compute the similarity of apps more effectively. As SimAndro does, SimAndro-Plus performs feature extraction and similarity computation steps; however, it has two major differences with SimAndro in the both steps as follows. First, instead of API-method and manifest-complete, SimAndro-Plus exploits two new beneficial features to similarity computation named as API-full-method and manifest-partial, respectively. API-method implicitly capture the app’s functionalities in some cases; for example, overloaded APIs are regarded as an identical feature, while they somehow perform different tasks. However, our API-full-method considers the API’s signature (i.e., API’s fully qualified name and its parameter list) as a feature, thereby capturing the app’s functionalities explicitly. Manifest-complete considers the app components (i.e., extracted from the AndroidManifest.xml file) as part of the feature, which are not predefined entities in the Android platform and exploiting them in similarity computation may be misleading; for example, declaring an activity component by two different apps cannot imply the similarity between the two apps since these activity components can be implemented to perform totally different tasks in each of the two apps. However, SimAndro-Plus does not consider app components as part of the feature by exploiting the manifest-partial feature. Second, in computing the similarity score between two apps based on their corresponding strings and package name features, SimAndro considers only the terms co-appearing in both apps; however, it has been shown that in computing the similarity between two objects of terms (e.g., documents), the number of those terms appearing in one object while missing in the other one is important as well [16]. Therefore, by following [16], SimAndro-Plus considers those terms appearing in one app while missing in the other one along with those terms co-appearing in both apps. The results of our extensive experiments with three real-world datasets and a dataset constructed by human experts (i.e., authors) demonstrate that SimAndro-Plus outperforms SimAndro.

The contributions of this paper are as follows:

- We extract two new helpful features from apps.
- In computing the similarity based on strings and package name feature, we not only consider those terms appearing in both apps but also consider those terms appearing in only one of the apps.
- We verify the last two contributions help to improve the accuracy of original SimAndro.

The rest of the paper is organized as follows. In Section 2, we briefly explain the existing methods. In Section 3, we present our SimAndro-Plus and its two orthogonal steps. Section 4 explains our experimental setup and analyzes the results of our experiments. In Section 5, we conclude our paper.
2. Related Work

In this section, we explain SimAndro and other existing methods. However, since we mainly focus on SimAndro in this paper, the other methods are explained briefly; the complete explanations about them can be found at [13, Section 2].

Reference [4] proposes a method for app recommendation where the similarity score of an app-pair is computed based on their titles and user comments. Reference [22] proposes a method to invoke users for replacing an already installed app $a$ with a new app $b$ where the similarity score between $a$ and $b$ is computed by exploiting their descriptions. In SimApp [5], the similarity between two apps is computed individually based on multiple features such as description, rating, permissions, and size; then, the obtained individual similarity scores are combined into a single value as the final similarity score. In reference [6], a method is proposed for automatically tagging apps where the similarity score of an app-pair is computed as in SimApp. DNADroid [7] detects app cloning by computing the similarity between apps based on different features such as title, developer, and description. All of the aforementioned methods extract the required features from the app stores, which might incur the problems of being inaccurate (e.g., permission list), varied in different app stores (e.g., description and user comment), unavailable (e.g., user comment and rating), affected by language barrier (e.g., description and user comments), and unappropriated for similarity computation (e.g., size and rating); exploiting these features may lead us to inaccurate similarity computation. These methods highly depend on the human explanations and descriptions of apps and neglect the useful features that can be mined from apps themselves and the Android platform [13].

SimAndro [13] is an effective state-of-the-art method to compute the similarity of apps by exploiting features extracted (i.e., mined) from apps and the Android platform itself; it is an easy-to-understand and straightforward similarity method for apps that can be applied to a wide range of applications such as app search engines, app recommendation, and app clustering. The motivation behind SimAndro is that apps contain helpful and unique features for similarity computation that clearly capture the apps functionalities without depending on the human explanations or descriptions of apps. SimAndro performs the two orthogonal steps of feature extraction and similarity computation. In the former step, API-methods, manifest-complete, strings, and package name are extracted as four different features from the classes.dex, AndroidManifest.xml, strings.xml, and AndroidManifest.xml files, respectively. We note that a typical app is an archive file type called Android Package (APK); this file is easily extractable by any archiving software and contain different folders (e.g., assets, lib, and META-INF) and files (e.g., AndroidManifest.xml, classes.dex, and strings.xml) [9] [13]. In the latter step, four similarity scores of an app-pair $(a, b)$ are calculated based on the aforementioned heterogeneous features separately. Then, by utilizing TreeRankSVM [1], the weighted linear combination of the above four scores is regarded as the final similarity score of $(a, b)$.

3. Proposed Method

Figure [1] illustrates an overview of our SimAndro-Plus. The overall process in both feature extraction and similarity computation steps are somehow similar to the ones in SimAndro; however, in order to make the paper self-contained, we briefly explain the two steps in this section along with the two major differences between SimAndro-Plus and its predecessor.
Fig. 1. An overview of SimAndro-Plus

3.1. Feature Extraction

In this step, we extract API-full-method, manifest-partial, strings, and package name from apps as four heterogeneous features where API-full-method and manifest-partial are two new features disregarded by SimAndro, while strings and package name are same as the ones exploited by SimAndro.

API-full-method Feature APIs in the Android platform are utilized by apps to interact with the underlying Android system and the device [8] [13]; for example, by calling the “android.os.Handler.removeMessages (int what)” API, an app removes pending messages with code “what” from the message queue. More specifically, API calls can clearly capture the app’s behaviors and functionalities [12] [13] [23]. Therefore, we extract the API calls as a feature to understand what operations an app executes. SimAndro considers the API’s fully qualified name as a feature called API-method (e.g., “android.os.Handler.removeMessages” for the above API). Let us consider the “android.os.Handler.removeMessages (I)” and “android.os.Handler.removeMessages (I, L)” APIs. Although these two APIs are different, they are regarded identical by the API-method feature. To solve this problem, SimAndro-Plus exploits a new feature called API-full-method that considers the API’s signature (i.e., API’s fully qualified name and its parameter list) instead of only the fully qualified name. As an example, for the two aforementioned APIs, “android.os.Handler.removeMessages (I)” and “android.os.Handler.removeMessages (I, L)” are considered as the API-full-method feature, respectively. API-full-method captures the apps functionalities more accurate than API-method since it considers the API’s parameter list as the part of the feature. In Section 4.2, we show that API-full-method is more beneficial than API-method to similarity computation.

To extract the API-full-method feature, we utilize both APK file and Android platform as follows. First, we mine the DEX file via it’s different sections such as the header, method_ids, string_ids, type_ids, proto_ids, and data. The method_ids section contains identifiers for all the app’s methods; the string_ids section contains identifiers for all the strings (e.g., classes, methods, parameters, etc.) in the app; the type_ids section contains

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Footnote: For simplicity, we use Dalvik symbols to represent parameters.
identifiers for all the types (classes and primitive types) defined by the app; proto_idx contains identifier for the return type and parameters of each method in the app; the header section defines the offset and the size of each of the aforementioned sections. Through the starting address of the method_ids section in the header, we read all entries in the section. Each entry in this section is a data structure that contains various kinds of information about a method including an index (class_idx) to an offset in the type_ids section, an index (name_idx) to an offset in the string_ids section, and an index (proto_idx) to an offset in the proto_ids section. The offset pointed by class_idx has an index to another offset in the string_ids section where we obtain the name of the method’s owner class. We also extract the name of the method itself through name_idx. The offset pointed by proto_idx has an index to an offset in other list contains number of parameters and their types. For each entry in the method_ids section, we concatenate its class name, method name, and parameter list to construct a candidate API-full-method. Then, we apply the Java reflection to the “android.jar” file to obtain a list of all API descriptions in the Android platform; if a candidate API-full-method does not belong to this list, we ignore it.

Finally, based on the API-full-method feature, an app is represented as a binary vector, A-vector, where each dimension corresponds to a feature value and the content of a dimension indicates the presence (i.e., value as 1) or absence (i.e., value as 0) of its corresponding feature value in the app [19]. In order to clarify it, suppose that \{a_1, a_2, ..., a_n\} is a set of n distinctive API-full-methods extracted from all the apps in a dataset; then, A-vector of app a is represented as \langle v'_0, v'_1, ..., v'_{n-1} \rangle with n dimensions where \( v'_i = 1 \) if a contains the feature value \( a_{i+1} \); otherwise \( v'_i = 0 \).

**Manifest-partial Feature** The AndroidManifest.xml file holds useful meta information (i.e., manifest information) about an app such as permissions, hardware/software components, app components (i.e., activity, service, broadcast receiver, and content provider), and intent filters (i.e., action and category); these information supports both installation and execution of the app [8] [13]. The permissions are required to perform critical tasks such as network access, the hardware/software components indicate either an essential or optional hardware (e.g., GPS) and software (e.g., VoIP) components that the app requires, the activity component implements a task with UI (user interface), the service component implements a background task without UI, the broadcast receiver component enables the app to receive events broadcast by the Android system or other apps, the content provider component supplies data access interface, and intent filters facilitates communication between the app’s components and also between different apps. This information can capture the app’s behaviors and functionalities as API calls do [2] [12] [13]; thus, we extract the manifest information as a feature for similarity computation.

SimAndro considers all the aforementioned information including the four app components as a feature called manifest-complete. An app component is defined by developers as a subclass of its specific standard class in the Android platform to implement the app’s specific functionalities. For example, although two activity components \( c_1 \) and \( c_2 \) from two different apps \( a \) and \( b \) are both defined as subclasses of the “android.app.Activity” class, they are developed with their own arbitrary names and under specific functionalities of \( a \) and \( b \), respectively; even if \( c_1 \) and \( c_2 \) are both activity components, they may not implement similar functionalities. More specifically, contrary to permissions, hardware/software components, action, and category, app components are not predefined enti-
ties in the Android platform and are developed independently for each app under the app’s specifications, thereby considering them as a feature may provide us inaccurate similarity scores. To solve this problem, SimAndro-Plus exploits a new feature called `manifest-partial` where only permissions, hardware/software components, action, and category are considered.

Based on the manifest-partial feature, an app is represented as a binary vector, \( M\)-vector, which is similar to \( A\)-vector. In Section 4.2, we show that `manifest-partial` is more beneficial than `manifest-complete` to similarity computation.

**Strings and Package Name Features** Furthermore, we consider strings and package name as two other features as SimAndro does. The strings.xml file is a single reference for various strings in an app where each string has a `name` attribute as its unique identifier [13, Fig. 3]; we extract both the string and its name attribute since the name attribute also represents some semantic information about the app. As an example, the following line in the strings.xml file of “Weather Forecast”, a free app for weather forecasting, defines a string:

```xml
<string name="weather_sunny">Sunny</string>
```

The package name located in the AndroidManifest.xml file is a unique identifier for the app and follows Java package naming convention. It is a combination of multiple terms (i.e., simple term or compound one) concatenated by dot and normally provides us abstract information about the app’s functionalities; for example, the “weather.widget.weatherforecast” is the package name of the “Weather Forecast” app. For each of these two features, we remove non-alphabetical characters, split compound strings (e.g., weatherforecast), remove stop words, perform stemming, and calculate the TF-IDF score [19] for each term. Finally, based on strings and package name features, an app is represented as two non-binary vectors \( S\)-vector and \( P\)-vector, respectively, where each dimension corresponds to a term and the content of the dimension is the TF-IDF score of the term.

**Feature Refinement** In order to obtain better accuracy in similarity computation, we need to perform a feature refinement. The reason is that some of the feature values are widely used in a large number of apps regardless of their functionalities, thereby exploiting them in similarity computation leads to inaccurate similarity scores. An as examples, consider the two following cases; the “android.os.Message.sendToTarget()” API used by an app to send a message to a specific handler is invoked in more than 90% of apps in our datasets, and the “INTERNET” permission allowing the Internet access is requested by more than 95% of apps in our datasets. We apply a feature refinement similar to the one in SimAndro to our new features, API-full-method and manifest-partial, as follows.

To refine the API-full-method feature with a dataset, we consider a threshold, \( T \), from 10% to 70% of the dataset size in step of 10% and a feature value is neglected if the number of apps in the dataset containing it is higher than \( T \); in other words, we do not consider those feature values that are common among more than \( T \) of apps. Then, we compute the apps similarity based on only the API-full-method feature refined with each value of \( T \) and compare the accuracy of these seven different cases; the \( T \) value of the case providing us the better accuracy is selected as the best value of \( T \). To refine the manifest-partial feature, we perform the same process.
3.2. Similarity Computation

As explained before, an app is represented by four different vectors as A-vector, M-vector, S-vector, and P-vector corresponding to its API-full-method, manifest-partial, strings, and package name features, respectively. As in SimAndro, to calculate the similarity score of an app-pair \((a, b)\) based on the API-full-method feature, \(A\)-score\((a, b)\), and the manifest-partial feature, \(M\)-score\((a, b)\), we apply Jaccard Coefficient (Jaccard) \([19]\) to corresponding A-vectors and M-vectors of \(a\) and \(b\), respectively. In the case of \(A\)-score\((a, b)\), it is calculated as follows:

\[
A\text{-score}(a, b) = \frac{\sum_i A^a_i \cdot A^b_i}{\sum_i A^a_i + \sum_i A^b_i - \sum_i A^a_i \cdot A^b_i}
\]  

(1)

where \(A^a_i\) and \(A^b_i\) denote the contents (i.e., 0 or 1) of the \(i^{th}\) dimensions in A-vector of \(a\) and A-vector of \(b\), respectively. We note that \(M\)-score\((a, b)\) is also calculated in the same way. We employed Jaccard to calculate these two scores since in the literature, it is a well-known similarity measure widely used to calculate the similarity of binary vectors (i.e., sets) in various topics such as image segmentation \([10]\), document summarization \([20]\), and similarity computation \([14]\).

On contrary to SimAndro, to compute the similarity score of an app-pair \((a, b)\) based on the strings feature, \(S\)-score\((a, b)\), and the package name feature, \(P\)-score\((a, b)\), we apply SMTP (similarity measure for text processing) \([16]\) instead of Cosine \([19]\) to corresponding S-vectors and P-vectors of \(a\) and \(b\), respectively, for the following reasons. S-vector and P-vector are non-binary vectors where each dimension corresponds to a term (i.e., a feature value) and the content of the dimension is set as its weight (i.e., the TF-IDF score). To calculate the similarity between two non-binary vectors, not only the proximity between the weights of co-appearing terms in both vectors but also the number of those terms appearing in one vector while missing in the other one is important as well. More specifically, as have been shown in \([16]\), 1) the presence or absence of a term is more important in similarity computation than the difference between the weights of a co-appearing term in both vectors; 2) the similarity score should increase when the difference between the weights of a co-appearing term decreases; 3) the similarity score should decrease when the number of terms appearing in one vector but missing in the other one increases. Let us consider three sample vectors \(i=<2, 0, 3, 0>, j=<2, 1, 3, 1>,\) and \(k=<2, 4, 2, 2>\). Although there are two missing terms in \(i\), the Cosine similarity score between \(i\) and \(j\) (i.e., 0.93) is higher than that between \(j\) and \(k\) (i.e., 0.78) where there is not any missing terms; Cosine does not acknowledge the third aforementioned case.

SMTP is an effective measure that considers all the three aforementioned cases in similarity computation. To calculate \(S\)-score\((a, b)\), we apply SMTP to the corresponding S-vectors of \(a\) and \(b\) as follows:

\[
S\text{-score}(a, b) = \frac{\sum_i N_i (S^a_i - S^b_i)^2 + \lambda}{\sum_i N_i (S^a_i - S^b_i) + \lambda}
\]  

(2)
the similarity computation (i.e., if $S_i^a = S_i^b = 0$, $\sigma_i = 0$).

$$N_s(S_i^a, S_i^b) = \begin{cases} 0.5 \times \left(1 + \exp \left(-\frac{\left(S_i^a - S_i^b\right)^2}{\sigma_i}\right)\right), & S_i^a, S_i^b \neq 0, \sigma_i \neq 0 \\ 0.5, & S_i^a, S_i^b \neq 0, \sigma_i = 0 \\ -\lambda, & S_i^a, S_i^b = 0 \\ otherwise \\ \end{cases}$$

$$N_{ij}(S_i^a, S_j^b) = \begin{cases} 0, & S_i^a, S_j^b = 0 \\ 1, & otherwise \end{cases}$$

where $S_i^a$ and $S_i^b$ denote the weights of the $i^{th}$ terms in $S$-vector of $a$ and $S$-vector of $b$, respectively. $\lambda$ denotes a constant and $\sigma_i$ does the standard deviation of all non-zero weights of the $i^{th}$ term in the dataset. Note that we regard an extra condition “$S_i^a, S_i^b \neq 0, \sigma_i = 0$”, which is not considered in the SMTP original formulation; if $\sigma_i = 0$, the SMTP definition is incorrect and the similarity score is undefined since the division by zero happens. $N_{ij}$ sums up the number of terms contributing in similarity computation.

The following three cases are considered through the four conditions in calculating $N_s$: 1) those terms co-appearing in both apps contribute positively to the similarity computation where the amount of contribution depends on the proximity of their corresponding weights in two apps and their standard deviations in the dataset (i.e., if $S_i^a, S_i^b \neq 0, \sigma_i \neq 0$). when the standard deviation is zero, the amount of contributions is less than the former case (i.e., if $S_i^a, S_i^b \neq 0, \sigma_i = 0$). 2) Those terms missing in both apps, do not contribute to the similarity computation (i.e., if $S_i^a, S_i^b = 0$). 3) Those terms appearing in one app but missing in the other one adversely affect the similarity score (i.e., fourth condition).

The similarity score of $(a, b)$ based on their package name features, $P$-score$(a, b)$, is also calculated in the same way as $S$-score$(a, b)$. In Section 4.2, we show that SMTP is more beneficial than Cosine to similarity computation of apps. Finally, as in SimAndro, we apply a weighted linear combination to combine the four scores into a single value as the final similarity score of $(a, b)$ as follows:

$$S(a, b) = w_1 \cdot A$score$(a, b) + w_2 \cdot M$score$(a, b) + w_3 \cdot P$score$(a, b) + w_4 \cdot S$score$(a, b)$$

where $w_1, w_2, w_3,$ and $w_4$ are weights to control the degree of importance of each score in the combination. We automatically find the best value of these four weights by utilizing TreeRankSVM [1] as a machine learning technique; more details can be found in [13, Section 3.3].

It has been shown that instead of considering all the above scores equally significant and simply summing up them into a single value as the final similarity score, applying a weighted linear combination to combine them contributes to obtain better accuracy in similarity computation [13]. We note that it also could be an option to simply combine our four heterogeneous features into a single one (i.e., each app is represented by a single binary vector) and then compute apps similarity based on this single feature; however, it has been shown that considering each of the four heterogeneous features separately in similarity computation is beneficial to obtain better accuracy [13].

### 3.3 Overall Process: Review

In this section, we present a simple review of the overall process required to compute the similarity between two apps as follows.
Feature extraction and refinement First, we use an archiving software (e.g., ark) to unzip all the apps in the dataset. Then, we extract the features for each app as follows. We mine the app’s classes.dex file through its different sections to extract API-full-method (in the case of SimAndro-Plus) and API-method (in the case of SimAndro); the mining process of the classes.dex file is described in Section 3.1 and Section 3.2.1 in detail. As an example, for the "WhatsApp Messenger" app, we extracted 5,398 feature values for API-full-method and 5,301 features values for API-method. Note that the API-full-method feature has more values since it considers the API’s parameter list as part of the feature. As an example, "WhatsApp Messenger" calls both of the two following APIs: the "android.media.MediaCodec.releaseOutputBuffer (int index, boolean render)" API is called to return an unnecessary buffer to the codec or to render it on the output surface, while the "android.media.MediaCodec.releaseOutputBuffer (int index, long renderTimestampNs)" API is called to update the surface timestamp of an unnecessary buffer and return it to the codec to render it on the output surface; API-full-method considers two various feature values for the above two APIs as "android.media.MediaCodec.releaseOutputBuffer (I, Z)" and "android.media.MediaCodec.releaseOutputBuffer (I, J)", respectively; however, API-method considers an identical feature value for both cases as "android.media.MediaCodec.releaseOutputBuffer". Next, we apply the feature refinement to both API-full-method and API-method features as explained in Section 2.1 where the best values of $T$ are 30% (i.e., refer to Table 2) and 20% (i.e., refer to [13, Table 4]), respectively, with the google dataset. As an example, we have 1,907 and 1,561 feature values for API-full-method and API-method, respectively, with “WhatsApp Messenger” after refining them as its final features.

Now, we exploit the AndroidManifest.xml file to extract manifest-partial (in the case of SimAndro-Plus) and manifest-complete (in the case of SimAndro); since this file is in the XML format, the feature extraction is straightforward and not tedious on contrary to that of the classes.dex file. For example, for the "WhatsApp Messenger" app, we extracted 85 and 97 values for manifest-partial and manifest-complete features, respectively. Note that the manifest-partial feature has less number of values since it does not take into account the app components (i.e., activity, service, broadcast receiver, and content provider). Now, we apply the feature refinement to both manifest-partial and manifest-complete features where the best values of $T$ are 30% (i.e., refer to Table 2) and 20% (i.e., refer to [13, Table 6]), respectively, with the google dataset. As an example, we have 64 and 74 values for manifest-partial and manifest-complete features, respectively, with “WhatsApp Messenger” after refining them as its final features.

Next, we extract the package name (e.g., ”com.whatsapp” for our sample app), decompose it into its constituent terms (e.g., ”com what app” for above case) by utilizing the Levenshtein algorithms [3], remove non-alphabetical characters and stop words, perform stemming on the terms, and measure the TF-IDF score of each term to obtain the package name feature. Finally, we extract the name attributes and their unique identifiers from the strings.xml file, remove non-alphabetical characters, split the strings, remove stop words including the Java reserved keywords as well, perform stemming on the remaining terms, and calculate the TF-IDF score of each term to obtain the strings feature.
**Automatic weight tuning** Each app is represented by four vectors as A-vector, M-vector, S-vector, and P-vector; in the case of SimAndro-Plus, these vectors correspond to the API-full-method, manifest-partial, strings, and package name features of the app, respectively, while in the case of SimAndro, they correspond to the API-method, manifest-complete, strings, and package name features, respectively. Now, we utilize TreeRankSVM to find the best values of $w_1$, $w_2$, $w_3$, and $w_4$ in Equation (3) automatically as follows; these values are later used to compute the similarity score of any app-pairs. We randomly choose 75% of the apps in the dataset to make a training set where each of the chosen apps is regarded as a *query* app. For each possible app-pair $(a, q)$ regarding to a query app $q$, we make a *hyperplane vector* (see [13, Section 3.3] for more detail) as follows:

$$\{r, qid, A\text{-}score(a, q), M\text{-}score(a, q), P\text{-}score(a, q), S\text{-}score(a, q)\}$$

when $r$ is set as 1 if $a$ is relevant to $q$ (i.e., $a$ belongs to the same category of $q$), otherwise 0 and $qid$ is a real number started from 1 denoting a query number. For both SimAndro-Plus and SimAndro, $A\text{-}score(a, q)$ and $M\text{-}score(a, q)$ are calculated by applying Jaccard to the corresponding A-vectors and M-vectors of $a$ and $q$, respectively. For SimAndro-Plus, $P\text{-}score(a, q)$ and $S\text{-}score(a, q)$ are calculated by applying SMTP to the corresponding P-vectors and S-vectors of $a$ and $q$, respectively; in these two cases, for SimAndro, Cosine is utilized instead of SMTP.

**Similarity computation** Let us consider two apps $a$ as "WhatsApp Messenger" and $b$ as "TalkU". To compute the similarity score of app-pair $(a, b)$, SimAndro-Plus employs Jaccard to calculate $A\text{-}score(a, b)$ and $M\text{-}score(a, b)$, employs SMTP to calculate $P\text{-}score(a, b)$ and $S\text{-}score(a, b)$, and finally applies the best values of $w_1$, $w_2$, $w_3$, and $w_4$ (i.e., obtained in the previous step) to Equation (3) to compute $S(a, b)$. SimAndro performs the same process; however, 1) $A\text{-}score(a, b)$ and $M\text{-}score(a, b)$ are calculated based on API-method and manifest-complete, respectively; 2) $P\text{-}score(a, b)$ and $S\text{-}score(a, b)$ are calculated by employing Cosine; 3) consequently, the best values of $w_1$, $w_2$, $w_3$, and $w_4$ are also obtained by a separate automatic weight tuning than the one performed with SimAndro-Plus.

To compute the similarity score between a *new* app and the existing ones in the dataset, we utilize the already identified values of $w_1$, $w_2$, $w_3$, and $w_4$. To update these values, we can follow some strategies; for example, if the number of new apps added to the dataset is 25% of the original dataset size (i.e., identical to our test set for the last automatic weight tuning), we perform a *new* automatic weight tuning on the dataset.

4. **Evaluation**

In this section, we carefully evaluate the effectiveness of our two contributions (i.e., exploiting the two new features and applying SMTP instead of Cosine) and compare the accuracy of SimAndro-Plus with that of SimAndro.

4.1. **Experimental Setup**

In order to conduct a fair evaluation, we employed the *same* datasets with SimAndro; *google*, *apkpure*, and *amazon* are three *real-world* datasets constructed based on the data
Table 1. Statistics of our datasets

<table>
<thead>
<tr>
<th></th>
<th>google</th>
<th>apkpure</th>
<th>amazon</th>
<th>manual</th>
</tr>
</thead>
<tbody>
<tr>
<td># apps</td>
<td>8903</td>
<td>11068</td>
<td>20570</td>
<td>444</td>
</tr>
<tr>
<td># categories</td>
<td>74</td>
<td>43</td>
<td>204</td>
<td>37</td>
</tr>
</tbody>
</table>

obtained by crawling Google Play Store, APKPure, and Amazon App Store, respectively. We constructed the manual dataset by selecting few apps from the three real-world datasets and carefully dividing them into various categories based on their functionalities. Table 1 shows the statistics of our datasets.

For the manual dataset, we can regard the categories as a ground truth set since the precise categorization is performed by humans expert (i.e., authors). For real-world datasets, their original categories are regarded as the ground truth sets since it is difficult and time-consuming to categorize them by humans expert (i.e., performing user studies); however, in order to conduct accurate and reliable evaluations, we consider a fine-grained categorization in our real-world datasets. For example, in our google dataset, the “Tools” category contains six sub-categories as “Alarm”, “Flashlight”, “Calculator”, “Input”, “Wi-Fi”, and “Recommended”; instead of considering all the apps in these six sub-categories under a single category as “Tools”, we consider these sub-categories as six distinct main categories as “Tools_Alarm”, “Tools_Flashlight”, “Tools_Calculator”, “Tools_Input”, “Tools_Wi-Fi”, and “Tools_Recommended”.

To evaluate the effectiveness, MAP, precision, recall [19], and PRES [18] are utilized as our evaluation metrics. In Equation 2, we set the value of $\lambda$ as 1 by following [16].

4.2. Results and Analyses

In this section, we refine our new features, compare the effectiveness of applying API-full-method, manifest-partial, and SMTP to similarity computation with those of API-method, manifest-complete, and Cosine, respectively. Finally, we compare the accuracy of SimAndro-Plus with that of SimAndro.

**Feature Refinement** As explained in Section 3.1, we perform a feature refinement for API-full-method and manifest-partial features with our four datasets through the same process as in SimAndro. Figure 2(a) illustrates the result of our feature refinement for API-full-method with the google dataset on top $k$ ($k=5, 10, 15, 20, 25, 30$) results; in the top of the figure, different values of $T$ and their corresponding line patterns are shown (e.g., $T = 30$ and $T = 60$ are represented with triangle and circle marked lines, respectively). As shown in Figure 2(a), the best accuracy in terms of MAP, precision, recall, and PRES is observed when the value of $T$ is set as 30% regardless of $k$; by setting $T$ to smaller values than 30% (i.e., 10% and 20%) or to larger values than 30% (i.e., 40%, 50%, 60%, and 70%), we would get lower accuracy. Figure 2(b) illustrates the result of the feature refinement for the manifest-partial feature with the google dataset on top $k$ results where the best accuracy is observed when the value of $T = 30%$ regardless of $k$. Table 2 summarizes the complete results of the feature refinement with all datasets.
Effectiveness Comparison of API-full-method and API-method  As explained in Section 3.1, we exploit API-full-method instead of API-method, which is one of the major differences between SimAndro-Plus and SimAndro. Now, we compare the effectiveness of API-full-method with that of API-method in similarity computation with our four datasets as follows. For each dataset, we employ the best values of $T$ for API-full-method from Table 2 and for API-method from [13, Table 4]; for example, with the google dataset, we set the best value of $T$ as 30% and 20% for API-full-method and API-method, respectively. Then, with each dataset, we apply Jaccard to compute the similarity of apps by exploiting only API-full-method and API-method features separately; in other words, we do not consider the other three features in similarity computation. Finally, we compare the results of these two similarity computations for each dataset where for simplicity,
the effectiveness is considered as the average of MAP, precision, recall, and PRES on different values of $k$. Figure 3 shows the results of this comparison; with all datasets, API-full-method shows better accuracy in terms of MAP, precision, recall, and PRES since it captures the apps functionalities more accurate than API-method by considering the API’s signature, while API-method considers only the API’s fully qualified name and neglects its parameter list. Table 3 represents the percentage of improvements in accuracy obtained by API-full-method over API-method with each dataset.

**Fig. 3.** Accuracy of API-full-method and API-method.

**Table 3.** Accuracy improvements(%) by API-full-method over API-method

<table>
<thead>
<tr>
<th>Dataset</th>
<th>MAP</th>
<th>Precision</th>
<th>Recall</th>
<th>PRES</th>
</tr>
</thead>
<tbody>
<tr>
<td>google</td>
<td>5</td>
<td>3</td>
<td>7</td>
<td>5</td>
</tr>
<tr>
<td>apkpure</td>
<td>4</td>
<td>4</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>amazon</td>
<td>3</td>
<td>3</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>manual</td>
<td>4</td>
<td>5</td>
<td>3</td>
<td>4</td>
</tr>
</tbody>
</table>

**Effectiveness Comparison of Manifest-partial and Manifest-complete** As explained in Section 3.1, SimAndro-Plus exploits the manifest-partial feature, while SimAndro exploits manifest-complete; this is another major difference between SimAndro-Plus and SimAndro. Now, we compare the effectiveness of these two features in similarity computation with our four datasets as follows. We employ the best values of $T$ for manifest-partial from Table 2 and for manifest-complete from [13, Table 6] regarding to the target dataset; for example, with the apkpure dataset, we set the best value of $T$ as 30% and 20% for manifest-partial and manifest-complete, respectively. Then, with each dataset, we apply Jaccard to compute the similarity of apps by exploiting only manifest-partial and manifest-complete features separately. Finally, we compare the results of these two

As an example, we compute MAP for $k=5, 10, 15, 20, 25, 30$; then, the average of these six values is considered as MAP.
Fig. 4. Accuracy of manifest-partial and manifest-complete.

Table 4. Accuracy improvements(%) by manifest-partial over manifest-complete

<table>
<thead>
<tr>
<th></th>
<th>MAP</th>
<th>precision</th>
<th>recall</th>
<th>PRES</th>
</tr>
</thead>
<tbody>
<tr>
<td>google</td>
<td>9</td>
<td>2</td>
<td>6</td>
<td>8</td>
</tr>
<tr>
<td>apkpure</td>
<td>11</td>
<td>1</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>amazon</td>
<td>7</td>
<td>9</td>
<td>8</td>
<td>7</td>
</tr>
<tr>
<td>manual</td>
<td>7</td>
<td>8</td>
<td>7</td>
<td>7</td>
</tr>
</tbody>
</table>

similarity computations for each dataset. Figure 4 illustrates the results of this comparison; with all datasets, manifest-partial shows better accuracy in similarity computation than manifest-complete in terms of all evaluation metrics. The reason is that manifest-complete considers app components in similarity computation; app components are not predefined entities and are developed independently in an app by developers under their own arbitrary names and functionalities, thereby considering them in similarity computation leads to inaccurate similarity scores. Table 4 represents the percentage of improvements in accuracy obtained by manifest-partial over manifest-complete with each dataset.

Effectiveness Comparison of SMTP and Cosine As explained in Section 3.2, SimAndroPlus applies SMTP instead of Cosine to compute the similarity between two apps based on their strings and package name features. We compare the effectiveness of these two measures in similarity computation as follows. For each dataset, we compute the similarity of apps by applying Cosine and SMTP to only each of strings and package name features separately (i.e., four different cases); then for each feature, we compare the results of two similarity computations obtained by employing SMTP and Cosine. Figure 5 illustrates the results of this comparison; in the case of both strings and package name features, with all datasets, SMTP shows better accuracy than Cosine. The reason is that, on contrary to Cosine, SMTP considers not only the terms (i.e., feature values) co-appearing in both apps but also takes into account those terms appearing in one app while missing in the other
Effectiveness Comparison of SimAndro-Plus and SimAndro  As shown in the last three sub-sections, considering API-full-method and manifest-partial as new features instead of API-method and manifest-complete, respectively, are effective; also, applying SMTP instead of Cosine to strings and package name features provides us better accuracy. These results imply that our both contributions are beneficial to similarity computation. As shown in reference [13], SimAndro outperforms existing methods proposed in references [5], [4], [22], [6], and [7]; therefore, here, we only compare the accuracy of SimAndro-Plus with that of SimAndro. More specifically, SimAndro-plus exploits API-full-method, manifest-partial, strings, and package name as four features, and applies Jaccard to the first two features and SMTP to the last two ones, while SimAndro exploits API-method, manifest-complete, strings, and package name as four features, and applies Jaccard to the first two features and Cosine to the last two ones. Figure 6 illustrates the results of this comparison with the four datasets; SimAndro-Plus outperforms SimAndro in terms of MAP, precision, recall, and PRES with all datasets. Table 6 represents the per-
percentage of improvements in accuracy obtained by SimAndro-Plus over SimAndro with each dataset; in average over all datasets, SimAndro-Plus outperforms its predecessor by 14%.

As another evaluation, we perform the same queries in reference [13] by employing SimAndro-Plus and compare their results with those of SimAndro as follows. We consider two well-known apps in the google dataset as “WhatsApp Messenger” with the package name “com.whatsapp” and “Opera Browser” with the package name “com.opera.browser” from categories “Social_Messenger” and “Communication_WebBrowser”, respectively. Then, we find out the 10 most similar apps to each of these query apps (i.e., result sets) by applying SimAndro-Plus as the similarity method. Table 7 shows the results where the Relevant column contains ✓ sign if the retrieved app is in the same category as the query; otherwise contains ✗ sign. Table 8 borrowed from reference [13] shows the results of the same queries with SimAndro. As shown in both tables, some apps are repeated under different signs in the Relevant column; the reason is that the google dataset assigns multiple categories to some apps. As an example, in the top result set of Table 7, the “Viber” app with the package name “com.viber.voip” is repeated three times where it is marked as relevant in rank 8 since it belongs to the same category as the query, and it is marked as irrelevant in ranks 9 and 10 since it belongs to other categories than the query’s category.

9 Viber is a cross-platform voice over IP and instant messaging software application provided by Japanese multinational company Rakuten.
Table 7. Result sets obtained by SimAndro-Plus for sample queries

<table>
<thead>
<tr>
<th>Rank</th>
<th>Package Name</th>
<th>Category</th>
<th>Relevant</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>me.talkyou.app.im</td>
<td>Social_Messenger</td>
<td>✓</td>
</tr>
<tr>
<td>2</td>
<td>me.talkyou.app.im</td>
<td>Communication_Messenger</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>kik.android</td>
<td>Social_Messenger</td>
<td>✓</td>
</tr>
<tr>
<td>4</td>
<td>com.bbm</td>
<td>Social_Messenger</td>
<td>✓</td>
</tr>
<tr>
<td>5</td>
<td>com.bbm</td>
<td>Communication_MovieChatting</td>
<td>✓</td>
</tr>
<tr>
<td>6</td>
<td>me.dingtone.app.im</td>
<td>Communication_Messenger</td>
<td>✓</td>
</tr>
<tr>
<td>7</td>
<td>me.dingtone.app.im</td>
<td>Social_Messenger</td>
<td>✓</td>
</tr>
<tr>
<td>8</td>
<td>com.viber.voip</td>
<td>Social_Messenger</td>
<td>✓</td>
</tr>
<tr>
<td>9</td>
<td>com.viber.voip</td>
<td>Communication_MovieChatting</td>
<td>✓</td>
</tr>
<tr>
<td>10</td>
<td>com.viber.voip</td>
<td>Communication_Messenger</td>
<td>✓</td>
</tr>
</tbody>
</table>

As observed by comparing tables 7 and 8, SimAndro-Plus provides us more accurate results than SimAndro with the both queries. In the case of the first query (i.e., “WhatsApp Messenger”) in Table 7, the “Kik Messenger” app with the package name “kik.android” in rank 3 and the “Viber” app in ranks 8, 9, and 10 are both messenger apps as “WhatsApp Messenger”, while they are absent in the result set obtained by SimAndro in Table 8. In the case of the second query (i.e., “Opera Browser”) in Table 7, the “Firefox Browser” app with the package name “org.mozilla.firefox” in rank 9 is a web browser as “Opera Browser”, while it is absent in the result set obtained by SimAndro in Table 8. More specifically, SimAndro-Plus fetches five similar apps for the both first and second query apps, while SimAndro does three and four similar apps for the first and second query apps, receptively.

5. Conclusions

In this paper, we proposed SimAndro-Plus to effectively compute the similarity of apps. SimAndro-Plus is an improved variant of SimAndro, the state-of-the-art method; however, it has two following major differences with SimAndro. First, SimAndro-Plus ex-
Table 8. Result sets obtained by SimAndro for sample queries

<table>
<thead>
<tr>
<th>Rank</th>
<th>Package Name</th>
<th>Category</th>
<th>Relevant</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>net.mobileinnova.whatsmon</td>
<td>Tool</td>
<td>×</td>
</tr>
<tr>
<td>2</td>
<td>me.talkyou.app.im</td>
<td>Social</td>
<td>✓</td>
</tr>
<tr>
<td>3</td>
<td>me.talkyou.app.im</td>
<td>Communication</td>
<td>Message</td>
</tr>
<tr>
<td>4</td>
<td>com.bbm</td>
<td>Social</td>
<td>✓</td>
</tr>
<tr>
<td>5</td>
<td>com.bbm</td>
<td>Communication, MovieChatting</td>
<td>×</td>
</tr>
<tr>
<td>6</td>
<td>me.dingtone.app.im</td>
<td>Communication, Message</td>
<td>×</td>
</tr>
<tr>
<td>7</td>
<td>me.dingtone.app.im</td>
<td>Social</td>
<td>✓</td>
</tr>
<tr>
<td>8</td>
<td>com.contapps.android</td>
<td>Communication, PhoneNumberBlocking</td>
<td>×</td>
</tr>
<tr>
<td>9</td>
<td>com.bsb.hike</td>
<td>Social</td>
<td>×</td>
</tr>
<tr>
<td>10</td>
<td>com.popularapp.fakecall</td>
<td>Productivity</td>
<td>×</td>
</tr>
</tbody>
</table>

Table 8. Result sets obtained by SimAndro for sample queries

<table>
<thead>
<tr>
<th>Rank</th>
<th>Package Name</th>
<th>Category</th>
<th>Relevant</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>com.opera.mini.native</td>
<td>Communication, WebBrowser</td>
<td>✓</td>
</tr>
<tr>
<td>2</td>
<td>com.apusapps.browser</td>
<td>Communication, WebBrowser</td>
<td>✓</td>
</tr>
<tr>
<td>3</td>
<td>com.fsecure.ms.dc</td>
<td>Tool, Recommended</td>
<td>×</td>
</tr>
<tr>
<td>4</td>
<td>com.superapps.browser</td>
<td>Personalization</td>
<td>×</td>
</tr>
<tr>
<td>5</td>
<td>com.explore.web.browser</td>
<td>Social</td>
<td>×</td>
</tr>
<tr>
<td>6</td>
<td>com.explore.web.browser</td>
<td>Communication, WebBrowser</td>
<td>✓</td>
</tr>
<tr>
<td>7</td>
<td>com.idotools.browser</td>
<td>Comics</td>
<td>×</td>
</tr>
<tr>
<td>8</td>
<td>nh.smart.opensign</td>
<td>Finance</td>
<td>×</td>
</tr>
<tr>
<td>9</td>
<td>mobi.mgeek.TunnyBrowser</td>
<td>Communication, WebBrowser</td>
<td>✓</td>
</tr>
<tr>
<td>10</td>
<td>com.chrome.beta</td>
<td>Productivity</td>
<td>×</td>
</tr>
</tbody>
</table>

exploits two new features as API-full-method and manifest-partial, which are completely disregarded by SimAndro. Second, in similarity computation based on strings and package name features, SimAndro-Plus considers those terms appearing in one app but missing in the other one along with those terms appearing in both apps by employing the SMTP measure instead of Cosine. The results of our extensive experiments with four datasets of apps demonstrated that 1) the both new features are beneficial to similarity computation, 2) employing SMTP provides us better accuracy than Cosine, 3) SimAndro-Plus outperforms SimAndro.

As a future research direction, we plan to investigate the effectiveness of applying SimAndro-Plus to the app recommendation systems. SimAndro-Plus can be regarded as a reasonable solution to address the item cold start problem [2] in app recommendation where new released apps (i.e., items) with no/few related information in the app store cannot be recommended to the users. The reason is that SimAndro-Plus compute the similarity between apps only based on the features extracted from apps themselves.

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References


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