Privacy-Aware Identity Cloning Detection based on Deep Forest

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Abstract. We propose a novel method to detect identity cloning of social-sensor cloud service providers to prevent the detrimental outcomes caused by identity deception. This approach leverages non-privacy-sensitive user profile data gathered from social networks and a powerful deep learning model to perform cloned identity detection. We evaluated the proposed method against the state-of-the-art identity cloning detection techniques and the other popular identity deception detection models atop a real-world dataset. The results show that our method significantly outperforms these techniques/models in terms of Precision and F1-score.

Keywords: Social-sensor cloud service provider · Identity cloning detection · Non-privacy-sensitive user features · Deep learning.

1 Introduction

Social sensing is a model that enables multiple social-sensors, such as humans, smart phones and smart glasses, to gather data [25]. This sensed data, often referred to as social-sensor data, can take various forms and be hosted on social-sensor clouds (i.e. social networks, e.g. Twitter and Facebook) [23]. Examples for such social-sensor data include Facebook status messages and Twitter posts. Social-sensor clouds are an important open medium that allows social-sensors/social media users to express their views on issues and events [2]. Critical information can be posted, especially descriptions and pictures of accidents or public activities [25]. Social-sensor clouds currently play an important role in special events (e.g. sports, crimes, etc.). Thousands or even millions of posts can be published by social-sensors (in text and/or in images), over social-sensor clouds. This large amount of information can be summarised as social-sensor cloud services (SocSen services) [23]. The special events can be represented from

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various points of view, such as where, when and what, by using the *functional* and *non-functional* properties of SocSen services [1].

The proliferation of social-sensor clouds has drawn plenty of attackers in the recent past. These attackers often seek to exploit the identities of *SocSen service providers* (i.e. social media information providers) and deceive users in a variety of ways. One such method of exploiting SocSen service providers’ identities is identity cloning in which an attacker registers a fake profile using the SocSen service provider’s identity information. Instances of identity cloning can be divided into two types: single-site and cross-site identity cloning [7]. The former applies to cases in which an intruder establishes a cloned persona of a SocSen service provider in the same social-sensor cloud whereas the latter refers to cases where an intruder steals a SocSen service provider’s identity from another cloud. Here, we primarily focus on single-site identity cloning detection.

Many identity cloning related crimes have occurred in the past few years. For instance, it has been reported that the Facebook Chief Executive Officer - Mark Zuckerberg’s Facebook account has been cloned and used in financial fraud [1]. In another well-known incident, the cloned Twitter account of Russian President Vladimir Putin has attracted over 1 million followers [2].

The majority of social-sensor clouds does not support automatic detection of identity cloning. For example, Twitter and Instagram, at present, investigate identity cloning reports after obtaining a valid identity cloning report from end-users. Automated methods to detect identity cloning are currently unavailable on these platforms [3]. Meanwhile, the majority of existing research on cloned identity detection uses *both* privacy-sensitive and non-privacy-sensitive user profile attributes. Due to privacy limitations, third-party applications cannot access privacy-sensitive user profile attributes such as the user’s full name, date of birth, or personal images available in social-sensor clouds through Application Programming Interfaces (APIs) or other means. As a result, most current techniques [13,19,20] for detecting cloned identities are potentially less applicable to third-party applications. Suppose an intruder uses a cloned account to log into the web or application of a third-party. Then, by using current techniques, this third-party will have difficulty determining with certainty whether or not the account is cloned. In contrast, non-privacy-sensitive user profile attributes, such as the user’s screen name, profile definition, and so on, are often readily available to third-party applications and can be directly accessed from the APIs exposed by social networking platforms. Hence, there is an apparent need and potential for exploring approaches to detect identity cloning by utilizing only non-privacy-sensitive user profile attributes.

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[1]https://www.nytimes.com/2018/04/25/technology/fake-mark-zuckerberg-facebook.html
[2]https://www.abc.net.au/news/2018-11-29/twitter-suspends-account impersonating-vladimir-putin/10569064
[3]https://help.twitter.com/en/rules-and-policies/twitter-impersonation-policy
[4]https://help.instagram.com/446663175382270
Moreover, the majority of current techniques detect cloned accounts using simple feature similarity \[13,15,19,20\]. Simple feature similarity is typically calculated using human-defined metrics such as TF-IDF-based cosine similarity or Jaro–Winkler distance \[13,15,18\]. These metrics are incapable of encapsulating the semantics of a wide variety of literal strings and focus only on character-distance or word frequency. For example, the above metrics cannot quantify the semantics of the terms *king* and *man* as a gender-based relationship. In such a setting, deep learning (DL), as an emerging technology, has demonstrated its overwhelming performance on executing big data processing and analytics tasks in diverse fields \[22\]. Nevertheless, to the best of our knowledge, using deep learning techniques to detect identity cloning remains to be explored. Therefore, we intend to fill this gap by investigating how DL could potentially be applied in the domain of identity cloning.

Though some DL models are powerful, they are not directly applicable/suitable for our application on detecting identity cloning. The reasons are two-folds. Firstly, most of the DL models require a large amount of training data. This is required to effectively learn a representation of a phenomenon associated with the underlying training dataset. Secondly, most DL models such as Deep Neural Networks (DNNs) have many hyperparameters that need to be fine-tuned as the learning performance of most DNNs depends on how well their hyperparameters are configured. This can often be a tedious and time consuming task \[29\]. In contrast, deep forest (DF) has a comparatively smaller number of hyperparameters that need tuning. Furthermore, the ability of DF to adaptively adjust the number of cascade levels required seems particularly an enticing feature by which the model complexity can be automatically determined. This enables DF to perform better on smaller data \[29\]. DF has also been shown to achieve competitive performance compared to DNNs in a variety of tasks \[29\].

To address the limitations in existing identity cloning approaches outlined above, we formalize the identity cloning detection task as a classification problem using multiple representations of two accounts (account pair) as input. We propose a novel approach for SocSen service provider identity cloning detection based on non-privacy-sensitive user information and a DF framework. Our main contributions can be summarized as follows:

- We propose a novel SocSen service provider identity cloning detection method for third-party applications by utilizing only non-privacy-sensitive user profile attributes accessible through social-sensor cloud APIs.
- We design multi-faceted representations to capture non-privacy-sensitive account features for effective identity cloning detection.
- We employ an effective DL model for cloned identity prediction. This is the first exploration on the application of DL in this problem setting.
- We conducted extensive experiments using a real-world dataset. The experimental results show that our method produces higher precision and F1-score compared to the state-of-the-art identity cloning detection techniques, the other machine learning-based techniques and the variants of our proposed method.
The rest of the paper is structured as follows. Section 2 reviews state-of-the-art identity cloning detection techniques. Section 3 presents the details of our proposed solution. Section 4 describes the evaluation of our proposed solution and discusses the results obtained. Section 5 concludes the paper.

2 Related work

A significant number of techniques had been proposed in the current literature to detect spammers or fake accounts on social networks [6]. The most commonly used techniques employ behavioural profiles of users that includes features such as writing style, accounts followed, etc., to classify users as trustworthy or untrustworthy [21,27]. However, the aforementioned features used in behavioural profiles cannot detect cloned accounts accurately because an attacker attempting to clone the identities can imitate those features. This demands finding features that are able to accurately characterize account pairs to detect cloned identities. Meanwhile, other works make use of trust relationships that exist between users in social networks to detect identity cloning. The main assumption of these methods is that a fake/spammer account cannot build an arbitrary number of trusted connections with legitimate accounts in social networks [4,21]. This assumption might not hold true in the context of identity cloning since attackers can attempt to imitate the profiles of legitimate. As a result, cloned accounts can build trust connections with legitimate accounts easier than other types of fake identities.

A few approaches have been proposed in the context of social media to detect identity cloning [5,6]. Kontaxis et al. [20] proposed a technique that can be used by social media users to determine if they have been a victim of identity cloning. Devmane and Rana [13] devised a method to detect identity cloning in both single-site and cross-site contexts. To detect cloned profiles, the aforementioned approach searches for similar user-profiles and then computes a similarity index. Jin et al. [18], in the meantime, analysed and characterised identity cloning attacks’ behaviours. They introduced two schemes for detecting suspicious profiles based on profile similarity. Kamhoua et al. [19] overcame identity cloning attacks by comparing user profiles across different social networks. They determined profile similarity using a hybrid string-matching similarity algorithm. Goga et al. [15] proposed a method for detecting impersonation attacks. The proposed method determines whether two accounts are being used by the same person or an imposter. It first compares the behaviour and reputations of impersonation accounts and then detects impersonation attacks using a binary classifier trained using a Support Vector Machine (SVM).

The majority of existing research [13,19,20] detects identity cloning using both privacy-sensitive and non-privacy-sensitive user profile attributes. Many third-party applications and websites authenticate users from their social networking profiles. They are unable to access privacy-sensitive user profile attributes through social network APIs. Therefore, prior approaches may not be applicable to these third parties. In addition, the majority of the existing ap-
proaches [13, 15, 18, 19, 20] are built on simple feature similarity models or classic machine learning models. DL technologies have shown their superior performance on processing and analyzing big data in many application domains [22]. To the best of our knowledge, there has been no attempt of applying DL technologies for identity cloning detection.

3 Methodology

In this section, we present a detailed overview of the proposed approach and its key components.

3.1 Overview

The proposed methodology is presented in Fig. 1, which consists of four major components, namely, 1) graph construction (GC) which aims to build an undirected graph from a given collection of social media accounts to identify the pairs of similar accounts; 2) an account pair feature representation, which extracts two categories of non-privacy-sensitive user features for each paired account; 3) a multi-view account representation, which constructs a representation for each account in an account pair from multiple non-privacy-sensitive perspectives; 4) a DF based prediction model, which predicts whether or not each account pair are an account and its replica using a concatenated representation of the account pair feature and multi-view account representations. We discuss these four components in detail in the following sections.

Fig. 1: The workflow of our proposed methodology

3.2 Graph Construction

Given a set of social media accounts and their profile information, we aim to construct an undirected graph, where each pair of mutually connected nodes indicate the possibility that an account is the clone of the other. A cloned account is more likely to share the same screen name or username with the original account.
Therefore, this graph connects nodes based on the screen name and username similarity. We connect two nodes with an edge only if the similarity score of the screen names or usernames of the two corresponding accounts is over a threshold $\delta$. This graph can locate almost all possible account pairs (i.e. a cloned account and its victim) in the dataset while generating fewer false positives with an appropriate $\delta$ value. We elaborate as well as make recommendations on the process of determining an appropriate value of $\delta$ in the forthcoming experiments.

3.3 Account Pair Feature Representation

Once the undirected graph is constructed, we then extract non-privacy-sensitive user features for each pair of connected accounts. The extracted features consist of two categories of non-privacy-sensitive user features in the form of 1) similarity-based features and 2) difference-based features that can differentiate a cloned account from a legitimate account. We describe each of these feature(s) in detail in the following subsections.

**Similarity-based features:** These features are used to analyse the textual similarity between the non-privacy-sensitive attributes of the profiles that belong to a pair of accounts, such as username, screen name, description and location. Each feature is assigned a value from the range $[0,1]$. For example, when the username similarity feature is 1, this indicates the pair of accounts compared has 100% textual similarity on the corresponding feature. In contrast, 0 indicates that the pair of accounts does not have any textual similarity on the given feature. We introduce the semantics of calculating the aforementioned textual similarity in more detail below.

**Username, screen name and location similarity:** Previous studies have shown that the Jaro–Winkler string similarity (JS) performs best on the attributes’ named values (e.g., username, screen name, or property name) [10][11]. Thus, we adopt JS, which is computed as the textual similarity between two strings as:

$$JS = \begin{cases} \frac{1}{3} \frac{m}{|S_1|} + \frac{m}{|S_2|} + \frac{m-t}{|m|} & \text{if } m > 0 \\ 0 & \text{otherwise} \end{cases}$$

where $m$ is the number of matching characters, $t$ is half the number of transpositions, and $|S_1|$ and $|S_2|$ are the lengths of both strings. Matching characters are the same characters in the two strings with a maximum distance of $w = \frac{\max(|S_1|,|S_2|)}{2}$. JS uses a prefix scale $p$, which provides a more specific result when the two strings have a common prefix up to a specified maximum length $l$.

$$\text{Jaro–Winkler} = JS + p + l \times (1 - JS)$$
Table 1: account pair feature representation and their descriptions

| Feature category          | No. | Features          | Description                                                                 |
|---------------------------|-----|-------------------|-----------------------------------------------------------------------------|
| Similarity-based features | 1   | Username similarity | Username similarity between the account pair.                               |
|                           | 2   | Screen name similarity | Screen name similarity between the account pair.                           |
|                           | 3   | Location similarity | Location similarity between the account pair.                               |
|                           | 4   | Description similarity | Description similarity between the account pair.                           |
|                           | 5   | Followers Ratio    | The ratio of the number of followers between the account pair.              |
| Differences-based features| 6   | Followers differences | The number of followers difference between the account pair.                |
|                           | 7   | Friends differences | The number of friends difference between the account pair.                  |
|                           | 8   | Tweets differences  | The number of tweets difference between the account pair.                   |
|                           | 9   | Favorite differences | The number of favorite difference between the account pair.                 |
|                           | 10  | Account age differences | The account age difference between the account pair.                        |

Description similarity: Users usually provide a short textual description of themselves in their social media profiles, which commonly shows their associations to organizations, occupations and interests. Therefore, we calculate the description similarity of the account pair. We first pre-process the textual description by converting to lowercase, removing stop words and punctuation marks. We then use term frequency-inverse document frequency (TF-IDF) to convert the text description into vectors. We then used the cosine similarity to find the similarity between two account descriptions as:

\[
\cos(\theta) = \frac{A \cdot B}{||A|| \cdot ||B||}
\]

where A and B are the TF-IDF scores of two accounts.

Differences-based features: These features are used to analyse the differences between the general profile attributes (e.g. the post count, friends count, etc.) that characterize individual accounts. We assume that the differences between the general profile attributes of a cloned account and its victim account will be higher than the other account pair. For example, a higher degree of differences between the number of tweets can indicate an avatar form of a pair of cloned and victim accounts.

Altogether, an account pair feature representation consists of 10 features across the two aforementioned categories, which are summarized in Table 1.

3.4 Multi-view Account Representation

Our objective is to construct a multi-view account representation for each account in the account pair by joining multiple views that correspond to the account’s non-privacy-sensitive profile attributes. We utilise the post, network, and profile attribute views associated with the user account. These views can accurately reflect a user account, which attackers are highly likely to mimic. Then, a single embedding is learned from these views using weighted generalized canonical correlation analysis (wGCCA) [17]. Each view is discussed in detail in the following subsections.
Post View: We obtain the pre-trained language representation for each account in the account pair to generate the post view. We use the Sentence-BERT (SBERT) [23] to obtain the user posts’ vector-space representations. SBERT is an adjustment of the pre-trained bidirectional encoder representations from the transformers network (BERT) [12]. These pre-trained models are extremely efficient at extracting the text representation associated with any given task such as question answering, classification, etc [12]. SBERT generates semantically meaningful sentence representations using Siamese and Triplet network structures. Similar to BERT models, SBERT models are also based on transformer networks [12]. Additionally, SBERT performs a pooling operation on the output of BERT in order to obtain a sentence representation with a fixed length. Typically, the sentence representation is computed by calculating the mean of all output vectors. We collect \( n \) posts that are publicly accessible for a given user account \( u \), denoted as \( T = (t_1, ..., t_n) \). Each post \( t_i \) \((i \in 1, ..., n)\) is represented by the language representation that is pre-trained. Each post \( t_i \) is tokenized into a single word \( w_i \) and then marked with special tokens called [CLS] and [SEP] to indicate the start and the end of a sentence, respectively. Then, a set of tokenized words is passed through BERT to embed fixed-sized sentences. Then, in the pooling layer, the \( t \) representations are generated using mean aggregation. The mean aggregation is known to perform better than max aggregation or CLS aggregation [23]. Each post’s output is 768 dimensions, which is BERT’s default setting. Finally, we aggregate all posts representation for the user account by computing the mean of all the posts’ representation \( T \).

Network View: A network of accounts is a collection of users who interact in a variety of ways, such as friending, retweeting, and so on, within a social network, which can be represented as a graph. If one of the users in the social network interacts (i.e. follow, retweet, etc.) with another, an edge between them will appear in the graph. We consider two types of interaction networks: follower and friend networks. In the follower network, two users will be connected when a user follows a specific user (e.g. a friend or celebrity). In the friend network, two users will be connected when a user gets followed by another user. Inspired by the graph representation’s success, we use the Node2Vec [16] to learn the network representation, or, in other words, the network view of an account. Node2vec is a widely used unsupervised graph representational learning technique. It utilises a biased random walk method to maximise the log-probability between a node’s neighbours, or in other words, accounts with an edge between them.

Profile Attribute View: We obtain 12 non-privacy-sensitive user attributes to create an attribute vector to construct the profile attribute view of an account. These non-privacy-sensitive user attributes can be used to categorise an account’s actions and credibility. For instance, the number of tweets may indicate a user’s activity, while the number of followers may indicate a user’s credibility. Table 2 shows the 12 non-privacy-sensitive user attributes.
Table 2: Features that profile attribute view contains and their descriptions

| No. | Features                        | Description                                                                 |
|-----|---------------------------------|------------------------------------------------------------------------------|
| 1   | Friend (following) count        | The number of accounts that the user follows.                                |
| 2   | Follower count                  | The number of followers that the account has.                               |
| 3   | Favorite count                  | The number of tweets liked by the account.                                  |
| 4   | Tweet count                     | The number of tweets (including retweets) posted by the account.             |
| 5   | List count                      | The number of public lists of which the account is a member.                 |
| 6   | Account age                     | The account’s lifetime to date, measured in months from the date of registration. |
| 7   | Profile background              | A binary value indicating whether or not the account has changed the background or theme of their profile. |
| 8   | Profile image                   | A binary value indicating whether the account has not uploaded a profile image and instead uses the default image. |
| 9   | Has profile description         | A binary value indicating whether or not the account has added a description to their profile. |
| 10  | Profile URL                     | A binary value indicating whether or not the account has added a URL to their profile. |
| 11  | Screen name length              | The length of the screen name of the account.                               |
| 12  | Description length              | The length of the description of the account.                               |

3.4.1 Embedding Learning Model

The proposed views in the previous section can include some helpful information that can be used to detect cloned accounts. Using each view separately can cause a loss of valuable knowledge in comparison to using them in tandem. A simple and naive technique is to concatenate all the proposed views together. However, this concatenation might cause over-fitting on small training datasets because of the resulting larger account representation or possibility of the resulting model ignoring the meaningful knowledge contained in the proposed views, as each view has unique statistical properties. Therefore, we employ generalized canonical correlation analysis (GCCA) which is a technique to learn single embedding from multiple views. GCCA has many variants, for example, [9,24,26]. In our proposed approach, we use Carroll [9]’s GCCA as it is based on a computationally simple and efficient eigenequation. The GCCA objective can be formulated as follows:

\[
\arg \min_{G, U_i} \sum_i \| G - X_i U_i \|_F^2 \quad \text{s.t.} \ G' G = I
\]

(4)

where \( X_i \in \mathbb{R}^{n \times d_i} \) corresponds to the data matrix of the \( i \)th view, \( G \in \mathbb{R}^{n \times k} \) contains all learned account embedding and \( U_i \in \mathbb{R}^{d_i \times k} \) maps from the latent space to the observed view \( i \). However, each view might have more or less knowledge for detecting identity cloning. As a result, we employ weighted GCCA (wGCCA). wGCCA adds weight \( w_i \) for each view \( i \) in Equation 4 as follows:

\[
\arg \min_{G, U_i} w_i \sum_i \| G - X_i U_i \|_F^2 \quad \text{s.t.} \ G' G = I, w_i \geq 0
\]

(5)

where \( w_i \) represents the weight of a view and this weight shows the view’s importance. The columns of \( G \) are the eigenvectors of \( \sum_i w_i X_i (X_i' X_i)^{-1} X_i' \) and the solution for \( U_i = (X_i' X_i)^{-1} X_i' G \).
3.5 Prediction Model

The final accounts pair representation $A_i$ is the concatenation of the account pair feature representation and the multi-view account representation.

$$y = \text{classifier}(\text{concat}(F, \text{wgcca})) \quad (6)$$

where $F$ is represented as a feature vector $F (\in \mathbb{R}^{10})$ where each feature $F_i$ in $F$ is indicative of an augmented feature derived based on the similarity or difference of a non-privacy-sensitive user profile feature and $\text{wgcca}$ is the embeddings learned from the multi-view account representation.

We employ DF to learn whether or not the account pair contains a cloned account and its corresponding victim account. The DF is a decision tree ensemble framework that can perform well even with relatively fewer data, and more importantly, has much fewer hyperparameters. The DF employs a cascade structure where each level of the cascade takes in a feature vector concatenated by its previous level and outputs its generating result to the next level of the cascade [29].

Diversity is highly recommended for ensemble construction [28]. Therefore, the proposed DF model uses two types of random forests (RF), extremely randomized trees (ERT) and logistic regression (LR). Fig. 2 shows the overall architecture of the proposed DF, which is of self-adapting depth with multiple levels. The RF model is an ensemble classifier which utilizes multiple decision trees at training time and uses averaging to get better prediction performance [8]. The ERT is similar to the RF model; however, they differ in the way splits are computed. The RF splits on trees while the ERT splits randomly [14].

In the first level of the DF architecture, each model will take the $\text{concat}(F, \text{wgcca})$ feature vector as an input and produce a class vector as output. This class vector is then concatenated with the $\text{concat}(F, \text{wgcca})$ feature vector to be fed into the next level of the cascade. Herein, we aim to predict a binary value $y$ indicating whether an account pair contains a cloned account and its victim. Therefore, each of the four models (2 RFs, ERT, LR) produces a binary output. Thus, the input of the next level of the cascade is composed of $8 (= 2 \times 4)$ augmented features. $k$-fold cross-validation ($k = 5$) is applied to generate the class vector. This
will result in $k - 1$ class vectors that are then averaged to produce the final class vector as augmented features for the next level of the cascade. After expanding one more level, the prediction performance of the whole cascade is estimated by the validation set. The cascade growth is automatically terminated if there is no significant increase in the performance of class prediction. Therefore, the number of cascade levels is said to be self-determined [29].

4 Evaluation

A set of experiments was performed to evaluate and analyse the effectiveness of our proposed solution against existing state-of-the-art identity cloning detection approaches. In addition, we also evaluated several candidate machine learning models to assess their performance in this particular problem context and justify the use of DF as the cloned identity predictor. All machine learning models were run for 10 rounds with different random permutations of the data. The results were presented as an average computed across the all rounds of experiments, together with standard deviation.

4.1 Dataset

To the best of our knowledge, there are no readily available and publicly accessible datasets for evaluating identity cloning detection in the context of social networks. Most existing works, albeit limited, have used simulated data to evaluate their proposed techniques. We, therefore, developed a dataset via authorised non-privacy sensitive user profile attributes fetched out of Twitter APIs in order to evaluate our proposed method. We collected 4,030 public Twitter accounts (2,015 cloned accounts and their corresponding victim accounts) from [https://developer.twitter.com/en/docs](https://developer.twitter.com/en/docs). We also randomly collected 20,152 public Twitter accounts to add noises to the dataset. Finally, we have 35,122 public Twitter accounts in total. The resulting dataset was randomly split with an 80:20 training-to-split ratio in order to derive training and test datasets.

4.2 Other Approaches Evaluated

We compared and evaluated our proposed approach against the following existing state-of-the-art identity cloning detection approaches [6] and variants of the proposed approach.

**Basic Profile Similarity (BPS) [18]:** This technique determines the degree to which a given user profile and its suspected cloned account share public attributes and common friends.

**Devmane and Rana [13]:** This technique compares names, education, profile photos, places lived, birthdate, workplace, gender, photos added to the profile, and number of friends/connections.

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5 [https://developer.twitter.com/en/docs](https://developer.twitter.com/en/docs)
6 [https://impersonation.mpi-sws.org/](https://impersonation.mpi-sws.org/)
Table 3: Hyperparameter values used for the candidate machine learning and DL algorithms

| Model | Parameter |
|-------|-----------|
| ADA   | estimators = 50 |
| CNN   | 10 layers, filters = 64, kernel size = 2, pool size = 2 |
| DNN   | 5 layers (250, 200, 50, 1) |
| KNN   | neighbors = 5 |
| MLP   | solver = adam, activation = relu |
| RF    | estimators = 50 |

**Goga et al. [15]:** This method compares profile similarity, social neighbourhood overlap, time overlap accounts, and account differences. It then trains an SVM classifier using a linear kernel to determine whether or not a given account has been impersonated.

**Kamhoua et al. [19]:** This method compares friend list similarity and calculates attribute similarity using a modified similarity metric called Fuzzy-Sim. To calculate the attribute similarity, it considers the following attributes: name, education, city, age, workplace, gender, and friend list. We used the same threshold values recommended by the original work (0.565 and 0.575) for the Fuzzy-Sim.

**Zheng et al. [27]:** This is a typical model for detecting spammers. It makes use of 18 features, some of which are profile-related, such as the number of followers, and others of which are content-related, such as the average number of hashtags. It then trains an SVM classifier using a Radial Basis Function (RBF) kernel to determine whether an account belongs to a spammer or not.

**GC (δ = 0.8):** This is a variant of our proposed solution that only feeds the results of the graph construction into the DF model.

**Account:** This is also a variant of our proposed solution that only feeds the account pair feature representation into the DF model.

**WGCCA:** This is also a variant of our proposed solution that only feeds the multi-view account representation into the DF model.

We further compared our proposed DF model against the following machine learning and DL models in order to justify the use of the DF as the identity cloning predictor. These models are broadly applied in the context of social media identity deception detection [6]. These models are, namely, Adaboost (ADA), Convolutional Neural Network (CNN), Deep Neural Network (DNN), K nearest neighbours (KNN), LR, Multi-layer Perceptron (MLP) and RF. In addition, we compared the proposed DF model with the other types of DF models (RF-based DF (DF$_{RF}$), ERT-based DF (DF$_{ERT}$) and LR-based DF (DF$_{LR}$)) to further justify the performance of the model.

### 4.3 Hyperparameter Tuning

All the hyperparameters of the supervised machine learning models were properly tuned to obtain their optimal performance. Table 3 shows the hyperpa-
Table 4: Comparison with the state of the art identity cloning approaches. Standard deviation (σ) is provided to the KPIs of our proposed solution and Goga et al.’s algorithm that were evaluated over 10 iterations.

| Model                      | Precision (σ) | Recall (σ) | F1-Score (σ) |
|----------------------------|---------------|------------|--------------|
| BSP [18]                   | 76.8          | 75.1       | 76.9         |
| Devmane and Rana [13]      | 66.3          | 68.1       | 67.2         |
| Goga et al. [15]           | 65.4 (1.1)    | 85.9 (1.5) | 74.3 (0.7)   |
| Kamhoua et al. [19]        | 68.2          | 70.1       | 69.1         |
| Zheng et al. [27]          | 68.15         | 73.34      | 70.64        |
| Our proposed solution      | 90.08 (3.42)  | 77.95 (1.69)| 83.52 (0.94) |

Parameter values used for the machine learning configured and (or) tuned the parameters as recommended in their respective original works. We also only used the non-privacy-sensitive user attributes provisioned by Twitter APIs. For our proposed solution, we find the optimal δ value of the GC is 0.8 according to the experimental results. We used ‘paraphrase-distilroberta-base-v1’⁷ as the pre-trained model for SBERT. This pre-trained model was trained on millions of paraphrase sentences. SBERT by default uses 768 as the dimension of its post representation. The default dimension of the Node2vec for both the follower and friend network is 128. We also used the probability of moving away from source node q = 2, the probability of returning to source node p = 0.5, the number of random walks per root node n = 10 and the maximum length of a random walk as 15. All the profile attribute views were normalized to [0, 1]. The weights w of the wGCCA were set as [0.25, 0.5, 0.5, 0.25] via experiments.

4.4 Results and Discussion

**Overall performance:** The performance comparison results are shown in Table 4. Our proposed solution yielded the best amongst the models compared against Precision and F1-Score. BSP [18] achieved the second best performance against Precision and F1-Score. Meanwhile, Goga et al. [15]’s proposed technique yielded the best-performing result on Recall. BSB [18] only employs profile attribute similarities and shared friends between account pairs. Goga et al. [15]’s proposed technique compares an account pair using only a traditional similarity technique and does not consider a filtering method for the account pair similar to our GC. The methods introduced by Kamhoua et al. [19] and Devmane and Rana [13] use a simple method to calculate profile attribute similarity. These techniques do not take into account the impact of the account’s posts and the account’s network information representation. Zheng et al. [27]’s proposed technique only takes into account a subset of features that compares spammer behaviour patterns. The obtained results indicate that our proposed solution is more suitable to a setting where only the non-privacy-sensitive user profile attributes are used for identity cloning detection in social media.

⁷https://huggingface.co/sentence-transformers/paraphrase-distilroberta-base-v1
Table 5: Comparison with the baseline machine and DL models evaluated as the predictor of our proposed solution. Each KPI is presented as an average over 10 iterations together with standard deviation (σ).

| Model | Precision (σ) | Recall (σ) | F1-Score (σ) |
|-------|---------------|------------|--------------|
| ADA   | 84.63 (1.49)  | 78.15 (1.49) | 81.26 (0)    |
| CNN   | 83.54 (0.41)  | 77.67 (1.87) | 80.49 (1.20) |
| DNN   | 85.66 (2.38)  | 76.68 (2.12) | 80.88 (0.42) |
| KNN   | 78.30 (1.49)  | 78.52 (0)    | 78.41 (1.49) |
| LR    | 84.64 (0)     | 78.15 (1.49) | 81.27 (1.49) |
| MLP   | 86.55 (3.81)  | 72.55 (3.69) | 78.83 (2.37) |
| RF    | 83.84 (0.27)  | 78.56 (0.12) | 81.12 (0.12) |
| DF RF | 84.16 (0.49)  | 78.82 (0.25) | 81.41 (0.34) |
| DF ERT| 83.98 (0.16)  | 78.44 (0.25) | 81.11 (0.06) |
| DF LR | 80.42 (0.43)  | 77.64 (1.32) | 79.01 (0.77) |
| DF   | **90.08 (3.42)** | **77.95 (1.69)** | **83.52 (0.94)** |

The comparison of results among the proposed DF model as well as other machine learning and DL models revealed that our DF model significantly outperformed all the other candidate models (see Table 5). We attribute this superior performance to two reasons. First, our DF model generates an ensemble of its base learners (i.e. RF, ERT, and LR) with a cascading structure where each cascade is an ensemble of the aforementioned base learners. Consequently, such a behaviour encourages diversity thereby improving its generalization performance eventually contributing to the significant increase in performance of our proposed solution. Further, the ability of DF to adaptively determine the best model complexity required for the problem context at hand also allows generating comparatively simpler models compared to the other approaches such as DNNs. This also helps improve the generalization performance of DF [29].

5 Conclusion and Future Work

We propose a novel SocSen service provider identity cloning detection approach based on non-privacy-sensitive user attributes. In the proposed approach, an undirected graph is first constructed to identify the pairs of similar SocSen service providers’ identities. We then extract an account pair feature representation. Afterwards, we also extract a multi-view account representation for each account. Then, these two representations are concatenated and fed into a DF classifier to predict whether or not a given account pair contains a cloned account. Our proposed solution was evaluated on a real-world Twitter dataset against other state-of-the-art cloned identity detection techniques and machine learning models. The results show that the proposed approach significantly outperformed the other models.

In the future, we plan to develop more effective identity cloning detection techniques and conduct experiments on large-scale datasets.
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