Identifying User Profiles Via User Footprints

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Abstract—User identification has been a major field of research in privacy and security topics. Users might utilize multiple Online Social Networks (OSNs) to access a variety of text, videos, and links, and connect to their friends. Identifying user profiles corresponding to multiple virtual activities of users across social networks is significant for the development of related fields, such as network security, user behavior patterns analysis, and user recommendation systems. In addition, predicting personal attributes based on public content is a challenging topic. In this work, we perform an empirical study and proposed a scheme with considerable performance. In this work, we investigate Reddit, a famous social network for questioning and answering. By considering available personal and non-personal attributes, we discuss our main findings based on mapping the different features such as user activities to a special user profile. We collected a dataset with wide distribution consisting of 5000 samples. To map non-personal attributes to personal attributes, a classification approach based on support vector machines (SVM), Random Forests (RF), and deep belief network has been used. Experimental results demonstrate the effectiveness of the proposed methodology and achieved classification accuracy higher than 89%.

Index Terms—User profiling, online social networks, text classification, deep belief network.

I. INTRODUCTION

With the widespread presence of online social networking sites (OSNs) and mobile devices, people are spending a lot of time on a variety of OSNs for keeping in touch with family and friends and using it as a source of information. A user might join multiple OSNs for different purposes. Understanding the patterns of users across different OSNs needs to identify the same user across multiple OSNs. For this problem, several methods were proposed such as an algorithm based on the multilayer perceptron. The features used for identifying are (i) user profile, such as name, location, and description; (ii) temporal distribution of user-generated content; and (iii) embedding based on user name, real name, and description. Identifying personal attributes age and gender, using users’ public content is an interesting problem among data scientists for two decades ago [1]. However, nowadays, we use the internet and digital devices in many aspects of our lives and generate a large amount of data. Thus, this constant generation of digital data provides opportunities to harvest and analyze ‘big data’ at an unprecedented scale and gain insights into an individual’s demographic attributes, personality, or behavior. Such information can be incredibly valuable to predict events, and future market, and reveals secrets e.g., predators with a false identity.

In recent years, the proposed solutions for identifying personal attributes usually have several steps including collecting data, preprocessing and cleaning data, feature extraction, feature selection, classification, and mapping between personal and non-personal attributes. Inferring individuals’ demographic attributes could be challenging depending on the availability of type and volume of users’ public content. It seems, that feature engineering, i.e., feature extraction and feature selection, are the most challenging steps and their difficulties are somewhat dependent on the type of data including text, image, and video. The most used data type is text which has been used for predicting various personal attributes e.g., age, gender, native language, and location [2]. There are a few works that have used images and videos to reveal personal attributes. For example, Wang et al. [3] used facial images to identify sexual orientation. Five useful methods for user profiling are proposed in [4], which refer to as Advanced Search Operator (ASO), Social Aggregator (SA), Cross-Platform Sharing (CPS), Self-Disclosure (SD), and Friend Finding Feature (FFF). By analyzing the similarities of k-hop neighbors to fully characterize the information redundancies in the friendship network the effect of similarities of user friendship networks in user identification across social networks was evaluated in [5]. In another research, a gradient descent algorithm is used to optimize the contribution of the user’s multi-hop nodes in the user identification process [6]. Also, the estimation of identifying user profiles in different online social networks by adding face recognition results to the model is improved [7]. In addition, identification of the psychological behaviors of users and extracting user opinions about products, movies, and foods from online social network (OSN) interactions are among the main interests of sentiment analysis and opinion mining studies [8]. A novel approach was proposed, named FEUI (Fusion Embedding for User Identification), by embedding the user-pair-oriented graph (UGP) through jointly integrating network structures, node attribute information, and node labels to achieve robust embedding features and predict node labels simultaneously [9]. An unsupervised scheme, termed Friend Relationship-based User Identification algorithm without Prior knowledge (FRUI-P) was proposed. The FRUI-P first extracts the friend feature of each user in an SN into the friend feature vector and then finds the similarities of all the candidate identical users between two SNs. In the last step, a one-to-one map scheme is developed to identify the users based on their similarities [10]. A novel trajectory-oriented method was proposed. At incorporating the locality-sensitive hashing (LSH) technology into the strategy of approximate nearest neighbors searching. An LSH function based on binary search (BLSH) for processing user trajectory easily, and by searching the BLSH buckets were designed. Finally, it clusters similar users to avoid the onerous full-scale pairwise comparison [11]. Another research used a one-dimensional residual network with squeeze-and-excitation (SE) configurations called the 1D-ResNet-SE model to investigate hand movements and user identification [12], the mediating effects of two distinct forms of user identification (i.e., user identification with the GSN brand and user identification with the GSN community) as well as the moderating effects of user global identity on the relationship between PBG and user engagement with such brands, investigated in [13]. A novel dataset is built in [14], which contains the writing characteristics of 160,000 users of the Twitter OSN. At the first step, feature transformation and feature selection methods are applied to determine the most relevant set of characteristics. To create the models, the Classifier Chain (CC) transformation technique and different machine learning algorithms are applied to the training set.
II. PROBLEM DEFINITION AND REDDIT PRIVACY POLICY

The aim of the assigned task is to identify Reddit’s usernames by analyzing non-personal data and mapping them to personal attributes. Non-personal data can be included in different types e.g., images, post content, videos, etc., and on the other hand, personal attributes can be those attributes which usually, users add during registration or update during their activation.

To know which attributes have been allowed by the policy privacy of Reddit, we study the relevant links provided by Reddit. In terms of non-personal attributes, users have been allowed to use user’s content including user’s photos, text, and videos, but they should not be modified. Moreover, API users should comply with any requirements or restrictions imposed on the usage of User Content by their respective owners. There are also some other restrictions for using Reddit API e.g., limiting the number of API requests by you may make or the number of users you may serve.

Challenges: Reddit is a massive collection of forums, where people can share news and content or comment on other people’s posts. Each user has two personal attributes: 1. the date of joining. Karma, which is a score based on written comments and posts 3. Number of received awards during the past 30 days (some users do not have this attribute). On the other hand, each user can have several posts and comments which can be used for extracting non-personal attributes. Posts and comments can include images and videos.

The main challenge is limiting the number of users which should be between 300 and 400 for the training set. Due to this limitation, feature engineering, as the main step for this task, would be more challenging and controvertible. We should extract some appropriate features from public data (posts and comments) which are mappable to personal attributes (joining date and Karma). For another limitation, Reddit API does not provide access to the whole public data of a specific user. This API returns at most 1000 new (or hot or top) posts (or comments) of a user. However, some users with high Karma usually have more posts and comments.

III. PROPOSED SCHEME

In this section, we describe the different steps of the proposed scheme. As shown in Fig. 1, the proposed scheme has five main phases including crawling data, preprocessing, feature extraction, classification, and mapping.

A. Crawling

As the first step, we found 500 usernames with different joining dates and Karma. To collect the data of each person, a script has been written which utilizes Reddit API and collects 15000 new (or hot or top) posts (or comments) for each person. We consider three types of sorting (new, hot, or top) to collect more posts (comments), but this notion may lead to repetitive data. By considering this issue, we remove the posts (comments) with the same IDs. The number of collected posts and comments for each person in the selected 16 users of the training set has been shown in Fig. 2.

B. Preprocessing

To extract effective features from collected data, we added a preprocess step to remove useless words from comments and posts. Therefore, for each post and comment we apply the following steps respectively:

1. Removing punctuations
2. Removing numbers
3. Ensuring all words are in lowercase
4. Replacing each word with its base form (lemmatization)
5. Removing stop words e.g., in, the, an.

To apply the abovementioned steps, we use NLTK which is a commonly used library for symbolic and statistical natural language processing.

C. Feature Extraction

We should extract some features from public data of users that are mappable to joining date and Karma logically. Users with more Karma usually have more posts and comments and maybe because of their experience, they write longer comments and posts. Therefore, we extracted the following non-personal attributes based on users’ posts and comments for each user:

1. Number of posts: total number of posts
2. Number of comments: total number of comments
3. total links: we detect the total number of links by searching in title and body of all user’s posts
4. YouTube links: we count the number of links referred to a video on the YouTube website by searching in all user’s posts
5. Image links: we count the number of links referred to a video on the imgur.com website (Reddit users usually use this website for importing an image in their posts) by searching in all user’s posts
6. Twitter links: we count the number of links referred to a video on the Twitter website by searching in all user’s posts
7. Average number of words in posts: we calculate the average number of words in the user’s posts
8. Average number of words in comments: we calculate the average number of words in the user’s comments
9. Date of the first post: The date of the first post of the user
10. Date of the first comment: The date of the first comment of the user

Fig. 1. The proposed scheme including five steps.

Fig. 2. The number of collected posts and comments for the selected users in the training set. The usernames show on the x-axis.
The last two features (date of the first post and date of the first comment) are not provided by Reddit API which consequently enforce us to use another API called PushShift. We can estimate the date of joining by having the date of the first user’s post (comment) with a high probability. Thus, a simple comparison between these two personal and non-personal features is required for mapping the two features. Other non-personal features are reasonable to be used for mapping to the Karma attribute. Obviously, users with a high number of posts will have high Karma. Moreover, high experienced users, which usually have higher Karma, write longer posts (comments) including links to other websites.

D. Classification

To map non-personal attributes to personal attributes, a classification approach has been used. One or several classifiers can be used to map 10 non-personal attributes to two personal attributes. To predict the joining year of users we have two options. First, we can simply use the date of the oldest post or comment of the user. This approach is very easy and we need a simple comparison. Second, to predict the joining year, we can use a classifier. We will implement both approaches and measure their accuracies. We also use another classifier to predict the Karma score.

To predict the Karma score based on non-personal attributes, we break down this score into three classes:

1- 0 – 100,000
2- 100,000 – 1,000,000
3- 1,000,000 – 15,000,000

Thus, the classifier which is responsible to predict Karma should solve a three-class problem.

Another classifier has been used to predict the joining date of the user. This feature has a range between 2006 and 2022, but we break down it into three classes as below:

1- 2006 – 2011
2- 2012 – 2016
3- 2017 – 2022

Like the previous classifier, this classifier will solve a three-class problem.

Regarding the type of classifiers, we will use two well-known algorithms called support vector machines (SVM) and Random Forests (RF).

E. Mapping

Two different approaches will be followed to predict the two personal features based on non-personal features. In the first approach called API1, we use the oldest date of the user’s post (comment) to predict the joining year and also feed the non-personal features to a classifier to predict the Karma score. It should be noted that, during collecting the user’s data, we save the first post date, thus, for each collection of data (including posts and comments content) we have the first post (comment) date. During the second approach called AP2, not only a classifier will be used for predicting the Karma score but also another classifier utilizes for predicting the date of joining.

To combine the results of these two classifiers, we use a simple sifting method here, the Sifting Profiles block in Fig. 4. First, we sift the profiles in which their joining date is matched with our predicted year (using AP1 or AP2 approaches). Then, we also sift the profiles whose Karma scores are in the class of the selected collection (we have three classes for Karma). Finally, we calculate common profiles between the two answer sets of previous steps.

F. Deep learning model

To map non-personal attributes to personal attributes, we use a deep-belief network model. In this method we run the model two times and predict the Karma amount of each user and the joining date of each one. The architecture of the model is shown in fig 5. A DBN is consist of RBMs, as basic blocks, and adds an SR layer that uses for multi-class classification problems [15]. By utilizing binary logistic regression, a SoftMax classifier is used to classify the feature vectors learned from hierarchical RBMs. For run DBN we faced two training steps: pretraining of each RBM, and a fine-tuning step. In the pretraining phase, each RBM is trained in an unsupervised procedure. This pretraining step is continued up to the SR layer. In the fine-tuning step, the whole DBN block is employed in a supervised procedure.

Fig. 3. The number of collected posts and comments for the selected users in the testing set. The usernames show on the x-axis.

Fig. 4. Mapping phase which uses two classifiers in parallel to select user profiles based on personal attributes.

Fig 5. Deep belief networks architecture including two RBM block and a SR block. RBM (restricted Boltzmann machine), SR (SoftMax regression)
IV. EXPERIMENTS

We use two algorithms i.e., SVM and RF, as the basic classifiers in our scheme. To adjust the best parameters for each classifier, we use two types of searching called Grid Search (GS) and Random Search (RS). GS can be thought of as an exhaustive search for selecting parameters’ model while RS sets up a grid of parameter values and selects random combinations to train the model. In the following subsections, we will investigate the results of the two abovementioned approaches i.e., AP1 and AP2.

A. AP1 Results

To map the joining date which is a personal attribute, AP1 uses the year of the first post (comment) and considers it as the year of joining. This technique does not have a training phase and gives the accuracy of 89% for training samples and 95% for testing samples. For the next step, a classifier will be trained to predict the Karma score. In fact, we use SVM and RF with two different ways of adjusting parameters (RS and GS). We split the training dataset into two parts of training and validation such that 70 percent of samples were considered as the training data. The accuracy for the validation set has been shown in TABLE I.

The best accuracy belongs to the SVM classifier which is used in Grid search for adjusting parameters (SVM-GS) and its confusion matrix has been shown in Fig. 5. It is worth mentioning that, we remove part of features including features 3-6 (See section III.C) to get better accuracy. We then feed the test dataset including 1600 collections (1600 persons) of data. The final accuracy is 80.5%.

B. AP2 Results

AP2 approach uses two classifiers sequentially to map non-personal attributes to personal attributes. The first classifier (C1) is responsible to decide about joining date and the second classifier (C2) determines the Karma score. All extracted features except 9-10 (including these features makes the learning process easy and logically is not correct) are used to train the C1 classifier. To obtain the best parameters, we split the training dataset into two sets i.e., training and validation sets, of which 70% of samples were considered for training. The performance of two used algorithms (SVM and RF) in place of C1 classifier has been shown in Fig 6 and Fig 7.

| Classifiers’ Name | SVM-RS | SVM-GS | RF-RS | RF-GS |
|-------------------|--------|--------|-------|-------|
| accuracy          | 0.71   | 0.80   | 0.76  | 0.78  |

Fig. 6. The confusion matrix of SVM-GS for the validation set to predict Karma.

Fig. 7. The confusion matrix of RF-GS for the validation set to predict joining year.

shown in TABLE II. The best performance has been obtained by RF-GS algorithm with an accuracy of 81%.

For the C2 classifier, we utilize the trained classifier during the AP1 phase i.e., SVM-GS. Therefore, we use the RF algorithm to predict the joining year and the SVM classifier will be used to predict the Karma score.

To evaluate the performance of AP2 strategy, we feed the testing data collections to the scheme.

C. DBN results

By using the DBN structure proposed in Fig 5 an accuracy of 89% for predicting Karma and the joining date is achieved. The confusion matrix of DBN for the validation set to predict Karma and joining date is shown in Fig 8. The best result in each step is illustrated in TABLE III.

| Classifiers’ Name | SVM-RS | SVM-GS | RF-RS | RF-GS |
|-------------------|--------|--------|-------|-------|
| accuracy          | 0.64   | 0.67   | 0.73  | 0.82  |

Fig. 8. The confusion matrix of DBN for the validation set to predict joining date(A) and Karma(B).
TABLE III
The best accuracy for predicting Karma score and joining date.

| Personal attributes | predicting Karma | joining date |
|---------------------|------------------|--------------|
| Classifiers' Name   | SVM-GS           | DBN          |
| accuracy            | 0.80             | 0.89         |
|                     | RF-GS            | DBN          |
|                     | 0.82             | 0.89         |

V. CONCLUSION AND FUTURE WORKS

Identifying user profiles is an important research topic. Moreover, user activities get distributed across many OSNs. Recently a lot of studies focused on this issue and they proposed different techniques. In this study, a combination of four methods and one deep learning model is proposed. The main goal is to map non-personal attributes to personal attributes and finally suggest the class of usernames. It seems the obtained accuracy is reasonable. However, there are some improvement solutions. For example, the third attribute of users’ profile, the number of received awards can be utilized to obtain more accurate performance. In addition, designing a deep model that can predict the exact amount of Karma will be useful.

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