2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining

Predicting Friendship Strength for Privacy Preserving: A Case Study on Facebook

Nitish Dhakal
Computer Science Dept.
Boise State University
Boise, ID 83702
nitishdhakal@u.boisestate.edu

Francesca Spezzano
Computer Science Dept.
Boise State University
Boise, ID 83702
francescaspezzano@boisestate.edu

Dianxiang Xu
Computer Science Dept.
Boise State University
Boise, ID 83702
dianxiangxu@boisestate.edu

***Abstract*—Effective friend classification in Online Social Networks (OSN) has many benefits in privacy. Anything posted by a user in social networks like Facebook is distributed among all their friends. Although the user can select the manual option for their post-dissemination, it is not feasible every time. Since not all friends are the same in social networks, the visibility access for the post should be different for different strengths of friendship for privacy. Previous works in finding friendship strength in social networks have used interaction and similarity based features but none of them has considered using sentiment-based features as the driving factor to determine the strength.**

In this paper, we develop a supervised model to estimate the friendship strength based upon 23 different features comprising of structure based, interaction based, homophily based and sentiment based features. We evaluate our model on a real-world Facebook dataset we built that has ground truth for different types of friendship: *close*, *good*, *acquaintance*, and *casual*. Our model obtains an AUROC of 0.82 in identifying acquaintances from all the other three categories, and an AUROC of 0.85 in distinguishing between close friends and acquaintances. Our experiments suggest that features like average comment length, reaction scores for likes and love, friend tag score, Jaccard similarity and closeness variable consistently perform better in predicting friendship strength across different classifiers. In addition, combining language-based features with homophilic, structural and interaction features produces more accurate and trustworthy model to evaluate friendship strength.

I. Introduction

Online Social Networks (OSN) are part of individual lives today. People are attached to many social networks such as Facebook, Twitter, and LinkedIn to express their opinions, preferences, pleasure and experiences. In each of these social networks, an individual may have many friends with different friendship strengths [1], [2]. This means that an individual friendship network contains both strong and weak relationships [3], [4], [5]. Since it is difficult to put both kinds of relationship into the same category, we need a mechanism to differentiate between weak and strong friends.

In OSNs, users can identify their important friends and organize by creating their own virtual social circle [1]. Facebook offers services to categorize the friends as acquaintances, family or spouses. Google plus also allows users to create the desired circle. However, in both of them, it is up to the users to differentiate the friends and put them into different circles.

It is natural that people try to maintain relationships by interacting with only those friends who they consider important. In Facebook, commenting on friend's profile, liking friend's posts, writing posts on the friend's wall and tagging friends are the most common modes of interactions among the individuals. With the introduction of new Facebook reactions like love, ha-ha, wow, sad, and angry emoticons, people have nonverbal options to express their opinions. Among all the friends of an individual, it is highly likely that friends with strong ties have most frequent of these kinds of interactions. Consider a Facebook user with 800 friends. There are only a few of them who has a trust relationship with the user and hence interact with the user regularly. There are friends who do not interact with the user at all. Some studies [6], [7] suggest that an individual in a social network is tightly connected to a small set of friends while loosely connected to a large group of friends. It is not beneficial for a user to share information with the group of friends who they do not interact at all [8]. People who participated in our survey mentioned this many times when they fail to notice the "friends" they have added on Facebook. They even unfriended the people later due to privacy concerns. This showed that people add friends in the social networks without even knowing them. Due to the open nature and popularity of OSNs, users are getting more and more concerned towards their privacy [9].

This paper tries to model these strong and weak ties and rank them according to four friendship categories named as *casual*, *acquaintance*, *good*, and *close* so that it is easier for automatic privacy assessment. More specifically, *close* friends are the ones you trust in real life, share information with, or somebody you are comfortable with. In other words, close friends are the best friends. *Good* friends are those who are not among the closest ones but who share a good bond. *Acquaintances* are the friends you have some familiarity with,

ASONAM '17, July 31 - August 03, 2017, Sydney, Australia

ACM ISBN 978-1-4503-4993-2/17/07?/$15.00
https://doi.org/10.1145/3110025.3116196

but not a personal relationship. They might be from your workspaces or from your schools. *Casual* friends are the ones you have just met on the social network and you do not have much information about them. These four friendship categories represent the degrees of friendship we considered in this paper.

In order to distinguish friendships of different strength for the user u, we first examine the total interactions made by all friends v with the user u. The interactions here represent reactions, comments, posts, tags, etc. exchanged between user u and friend v. It is worth noting that the interaction may be positive or negative. The polarity of the interactions between the user and a friend is determined in our model by doing sentiment analysis on the comments exchanged between the friend v and the user u. On doing this, we would evaluate the strength of the connection between the user and their friends. Existing research have modeled the friendship strength in social media using interactions and similarity data [1], [4], [10], [8], [11], [12], [13]. Other researches have used interaction data exchanged between the user and their friends to predict the friendship strength [14], [15]. However, none of them has considered sentiment analysis for determining friendship strength. Thus, this paper aims to tackle this unique problem. Research on social networks suggests that the bond of friendship can also be predicted from the network they are embedded in [16]. Therefore, besides the sentiment-based features, we also take advantage of the network structural features shared between the user and their friends.

In this paper, we develop a friendship strength model that is a function of interactions, sentiment, structural and homophilic variables. This model combines the existing interaction and similarity features with the new set of sentiment-based features, some of them inspired by existing work [17], and uses them to fit into different classifiers. The model seeks to find the features that work best in classifying strong relationship from weak ones on Facebook. Our contribution in this paper is threefold. First, we are the first one to discuss the sentiment-based features in determining friendship strength. Second, we study for the first time friendship strength across four different friendship categories, namely close, good, acquaintance, and casual. Third, we have extracted a *new* dataset of 680 user-friend pairs in Facebook with ground truths. Experimental results show that our model is able to identify acquaintances from all the other three categories with an AUROC of 0.82 and distinguish between close friends and acquaintances with an AUROC of 0.85.

II. Friendship Strength based Privacy Model

One application for automatic friendship strength classification is to decide visibility levels on user's created activities. Currently in Facebook whenever a user writes the post, the post is disseminated to all user's friends (named as public). If a user is concerned about the privacy of the post, one measure user can apply is to select the friends manually or post it to the particular groups the user has already classified. In real life, the visibility access for the post should be different for close, good, casual and acquaintances. A family photo posted by the user would like their close friends to view and interact with the post while a more general trending topic, a user would want his casual friends to interact more.

Therefore, if a system does the privacy assessment automatically then it would be easier from user's perspective. Based upon the effectiveness and context of the model, the user could be given a warning or could be given the option to set the visibility level before posting it on the social network.

III. Related Work

A. Predicting Friendship Strength in Social Networks

Finding tie strength in online social networks is not a new task. However, the use of sentiment-based features is novel. A close work is the one by West et al. [16] on signed social networks where they use both network structure and sentiment analysis to predict like/dislike opinion of a user u towards another user v. Their work and ours' are different in the sense that they try to predict user u's opinion about v, and is more focused on opinion analysis rather than friendship strength.

Gilbert et al. [4] tried to cover various aspects of the relationship in the social network; however, their model did not consider the sentiment analysis as the emotional factor driving the friendship strength. Their model considered about 70 numerical indicators describing the tie strength among friends on Facebook on a dataset of about 2000 Facebook friends and classified with 85% accuracy. Besides the sentiment analysis, our model is different from them in terms of social distance variables (like occupation, education, political view). They have designed their model by taking the differences among these variables (between the user and a friend) as a feature but we assume the similarity between the variables as features. Since differences were more likely to happen, we thought similarity would make our feature strong.

Similarly, Tanbeer et al. [10] tried to seek and rank influential friends. Zhang et al. [12] have studied tie strength in mobile communication networks by taking reciprocity of calls between the users under consideration. Onnela et al. [11] have also studied tie strength in mobile communication networks by considering network structure. There has also been a study on finding tie strength in musical social networks based upon the similarities of musical tastes in Last.fm [13]. Likewise, there have been research projects in the past where data mining techniques have been utilized to find a strong group of friends [18], popular friends [19], and significant group of friends across multiple domains in social networks [20]. These research projects take a number of messages posted by users in Facebook into account but do not consider other interactions among the user and their friends.

Akbas et al. [1] did a similar project as ours but they tried to generate friend ranking based upon the user interaction in the mobile phone. They considered calls, voice messages, and chats as the factors of interaction. They have ranked the user friends by using "Sports Ranking Algorithm" by giving weights to different types of interactions that happen in user phone. Their research and this paper have similar problem formulation while giving weights. Xiang et al. [8] research on Online Social Networks is similar to this paper in terms of the goal of distinguishing strong friends from weak ones in social media. They use unsupervised approach (rather than our supervised approach) using a latent variable model to infer (hidden) relationship strengths. However, they do not consider polarity of interaction as the feature.

Our work on finding tie strength closely relates with Jones et al. [5] where the researchers asked the number of individuals about who their close friends are in real life. Based on the interaction in between the survey users and their real world friends (ground truth) done on Facebook they could successfully discriminate close friends from not so close friends. However, they have limited their work in just finding closest friends among others. In addition, they have not done sentiment analysis at all.

Another work close to ours is Arnaboldi et al. [21] where the researchers have analyzed the user friend relations among 28 users and their 7103 relationships. They did a survey like ours and asked the participants to rate their Facebook friends from 0 to 100 score. Their model is limited to regression analysis of the friendship strength and statistical analysis of datasets.

B. Privacy Preserving in Online Social Networks

Different online social networks have utilized the concept of trust and privacy preservation in the past. Golbeck [22] developed a recommendation system model on FilmTrust network by utilizing trust among the users as a principal factor in the algorithm. The trust among the friends was generated from their interactions. In our model, we have used different facets of interactions and relationships between the user and their friend to determine the trust.

Izzat et al. [23] have done research on a trust and reputation model for social networks. Their work concerned on finding a reputation score based on the personal attributes and relational attributes of the user. Personal attributes included work, education, interest groups, favorites etc. Relational attributes included personal activities like quality and quantity of interactions with other friends and characteristics associated with the individual friends. These characteristics may be a number of interactions made by the user or their individual reputation level. Their proposed reputation model aims at preserving the user's privacy and is adaptive to the changes in user's reputation score over time. Although the application of our model and their model seems to be same, we have developed a machine-learning model with different classes of friends derived from ground truth. Our main works revolve around the model using different aspect of interactions, sentiment, structural and homophilic features. One of the applications of our model is privacy assessment as explained in Section II.

Our model can also be used as a component in work done by Cho et al. [24]. They have utilized the concept of trust and reputation to preserve the user's privacy on one hand while also increasing social capital in OSNs. Their trust model encapsulates the individual user's interactions with other users based upon user's posts, friend's likes, and comments. Our model can be used for providing more reliability to their trust model. Their trust and reputation model has not been done tested in real world dataset yet while our trust based model has utilized real world dataset.

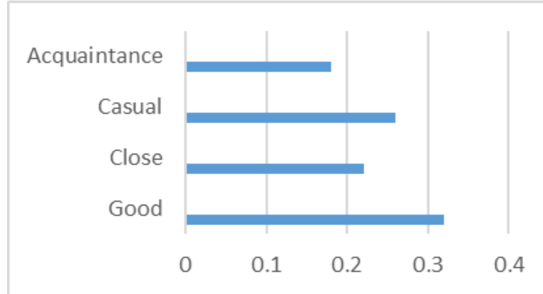

Fig. 1: Average percentage of occurrence of different categories of friends.

IV. The BSU Facebook Dataset

To test our model we set up an online survey to collect data. We sent out a mass email to about 2,000 students studying at Boise State University[1]. We selected students whose primary speaking and written language was English. The motivation was that the model used to extract the comments sentiment is trained on English datasets. Among the emailed students, 54 of them replied and agreed to be part of the survey.

In the period of about a month and a half, we crawled the Facebook pages of the participants to extract the following data: list of friends, friends of friends, profile information, posts, interests, and group memberships. We crawled information only from *wall posts* that were public. Also, due to the individual privacy settings, the user profile information like gender, contact information, profession, and user education information was limited to the ones that are public. We collected a dataset of 316K nodes, 382K edges, and 18K posts.

To collect ground truth about friendship strength, we presented a survey to each participant containing 20 friends and asked them to classify their friends under the four categories we considered: *close*, *good*, *acquaintance* and *casual*. For each participant, the 20 friends were selected as the top-20 friends who interacted the most with the participant on Facebook. Only 34 completed the survey within 15 days and we got a total of 680 edges with ground truth.

Fig. 1 shows the average percentage of occurrence of *close*, *good*, *acquaintance* and *casual* friends among the 34 users in our dataset. From this figure, we can see that most of the users have a greater number of good friends than the casual and acquaintance. The percentage of an average number of good friends is highest and is about 32%. While the percentage of the average number of acquaintance is the lowest and is about 18%. The percentage of close friends and casual friend is 21% and 26% respectively.

One of the interesting things we found from the survey was that almost every user failed to recognize at least one of their Facebook friend presented to them. This tells us that people have the tendency to add unknown persons on Facebook.

[1]Our research was authorized by the Institutional Review Board (IRB) committee at Boise State University.

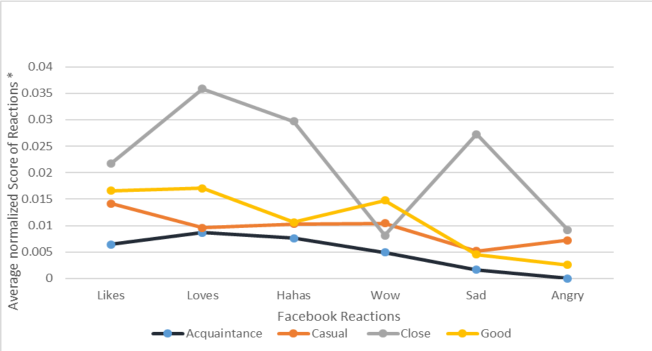

Fig. 2: Average normalized score of Facebook reactions among different categories of friends.

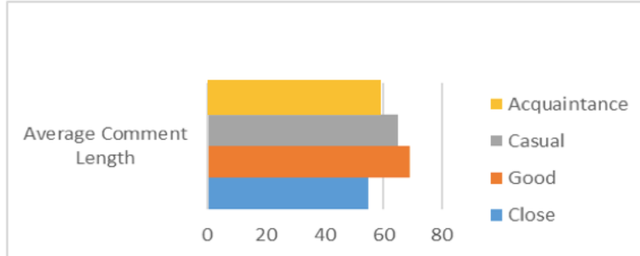

Fig. 3: Average comment length among different categories of friends.

V. Friendship Strength Model

We study friendship strength by considering four classes of variables, namely *general interactions*, *sentiment-based features*, *structural features*, and *homophily features*. Details about these variables are presented below.

A. General Interactions

Whether the user has strong or weak friends, they react to the posts that user share on their walls. Reactions include nonverbal ways of expressing the opinions like giving *likes, love, wow, haha, sad* or *angry* emoticons. This is the most used way of friend interaction on Facebook. Prior to this research, there have been no studies in Facebook reactions. We assume that the more such “Facebook reactions”, the more intense is the friendship strength between the user and their friends. It is highly likely that weak friends have a weak level of such interactions.

From our dataset, we found that *close* friends usually tend to give more *love* emoticon and very few *angry* emoticons. On the other hand, *likes* were seen as the most common mode of interaction between all category of friends. Fig. 2 shows the average normalized score of different Facebook reactions across different categories of friends. From the figure, we see that reactions like *loves, like, haha* and *sad* are high among the *close* and *good* friends and low among the *casual* and *acquaintances*.

Therefore, we consider each of these different types of reactions as a different feature. Given a reaction $\ell \in \{likes, love, wow, haha, sad, angry\}$, we define the *Reaction Score (RS)* between a user u and a friend v as

$$RS(u, v, \ell) = \frac{R_\ell(u, v)}{R_\ell(u)}$$

where $R_\ell(u, v)$ is the total number of reactions of type ℓ given to the user u by the friend v , and $R_\ell(u)$ is the total number of reactions of type ℓ given by all friends to u.

There is also the tendency of tagging friends or being “tagged” in Facebook posts. We identify this as another feature in our model, as, when a user tags a particular friend, it means that the friend is highly important to the user. As we observed in our dataset, people often tag their *close* or *good* friends. Let $tags(u, v)$ be the number of times user u tagged the user v. We define the *Friend Tag Score (FTS)* as the ratio of $tags(v, u)$ (number of tags from friend v to user u) to the total number of tags done to user u by all friends of u (denoted by $tags_{\mathcal{F}(u)}(u)$):

$$FTS(u, v) = \frac{tags(v, u)}{tags_{\mathcal{F}(u)}(u)}$$

As another feature, we also consider the *User-Friend Tag Score (UFTS)* as the ratio of the number of tags the user u has done to a particular friend v ($tags(u, v)$) to the total number of all the tags done by the user u to all u’s friends (denoted by $tags_u(\mathcal{F}(u))$):

$$UFTS(u, v) = \frac{tags(u, v)}{tags_u(\mathcal{F}(u))}$$

In addition, we observe that different friends write comments of different lengths. Fig. 3 shows the average comment length across the four different friend categories. According to the figure, the average comment length of good friends is a bit higher than other categories, so we use the *average comment length* among all posts written by a friend to user u’s wall as a feature for friendship strength classification.

B. Sentiment-based Features

In this second group of features, we consider the sentiment of comments given by a friend v on user u’s wall. Comments’ sentiment analysis is performed by using the VADER library [25]. VADER is a parsimonious rule-based model, which works effectively with the social media texts and proves to be effective with the slangs and acronyms very well. For a sentence or comment, VADER gives a negative, positive, neutral and compound score. We have considered comments as positive if the VADER compound score is > 0.1 and negative when the score is < -0.1. We consider the score between 0.1 and -0.1 as neutral sentiment score.

1) Comments Polarity: We assume that if a friend gives positive comments, then the friend has a positive interaction with the user and if they give negative comments then they have a negative interaction with the user. The *Comments’ Polarity Score (CPS)* between users u and v is determined by the ratio of net comments (positive − negative) to the number of overall comments shared between user u and a particular friend v. More specifically,

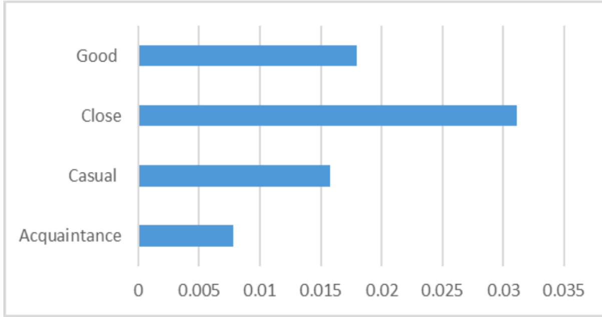

Fig. 4: Average Jaccard similarity among different categories of friends.

$$CPS(u,v) = \frac{|pos(u,v)| - |neg(u,v)|}{|comments(u,v)|}$$

where $pos(u,v)$ (resp. $neg(u,v)$) is the set of positive (resp. negative) comments written to the user u by a friend v, and $comments(u,v)$ is the set of all comments shared between users u and v.

2) Contradiction and Agreement Rank: We consider the notions of contradiction and agreement rank proposed in [17] and adapted them to our case.

Contradiction rank gives the disagreement of the user towards another user. The higher the contradiction rank, the higher the disagreement between a user pair. Let x^+_{uv} be the fraction of the positive comments given to the user u by a friend v. Let x^-_{uv} be the fraction of the negative comments given by the same friend v to u. Similarly, we define y^+_u and y^-_u as a fraction of all the positive and negative comments shared to user u. Hence, the contradiction rank between u and v is given by

$$CR(u,v) = x^+_{uv} y^-_u + x^-_{uv} y^+_u$$

For example, if the friend v gives 1 positive comment out of 4 then x^+_{uv} = 1/4 and x^-_{uv} = 3/4. Suppose, instead, all u's friends think positively towards u, making y^+_u higher, say 5/7 so y^-_u is 2/7. Then, the contradiction rank between u and v is $CR(u,v) = (1/4) \times (2/7) + (3/4) \times (5/7) = 0.61$ which says that there is a high contradiction between the user u and the friend v.

Unlike the contradiction rank, the *agreement rank* gives the degree of agreement between users. Intuitively, the higher the agreement rank, the higher the agreement between users and hence stronger the bond. For same parameters x^+_{uv}, x^-_{uv}, y^+_u and y^-_u, the agreement rank is defined as

$$AR(u,v) = x^+_{uv} y^+_u + x^-_{uv} y^-_u$$

If we consider the values of x^+_{uv}, x^-_{uv}, y^+_u and y^-_u as in the above example, we have that the agreement rank between users u and v is given by $AR(u,v) = (1/4) \times (5/7) + (3/4) \times (2/7) = 0.39$ which says that there is a low agreement between the user u and the friend v.

3) Closeness Variable: Upon evaluating the comments in our dataset, we see that individuals express their opinions like *"☺ Great picture honey!"*, *"Our heart hurts with urs"*,*"A huge hug :)"*, *"Ohh dear"*, *"Wooow honey so happy for you.. that's amazing ..!! Skype soon xxx ?!!"*, etc., to show their attachments to their friends (mainly close and good). Thus, we computed the set of unigram, bigram, and trigram from the comments we have in our dataset and selected as keywords the ones whose sum of frequency for close and good friends is greater than 80%. These keywords include *Love you, :) , miss you , happy birthday, honey, xoxo, i love you, babe, dude, etc.* From this set of keywords, we produce another feature called *closeness feature* which is a binary value representing the presence or absence of at least one of these closeness signifying words in the comments exchanged by a pair of friends.

C. Structural Features

The strength of friendship between users also depends upon the network they are included in. Intuitively, if the two users share a large number of common friends, then it is likely that they have a stronger bond. Similarly, a low number of common friends would mean that there is a weaker bond between the users. Thus, we consider, as feature in our model, the *Jaccard Similarity (JS)* between user u and a friend v defined as

$$JS(u,v) = \frac{|\mathcal{F}(u) \cap \mathcal{F}(v)|}{|\mathcal{F}(u) \cup \mathcal{F}(v)|}$$

where $\mathcal{F}(u)$ is the set of friends of user u. Fig. 4 shows the average structural similarity scores across different categories of friends. We see that close friends tend to have more friends in common than good friends. Causal friends also have fewer friends in common than the acquaintance's, which have the least score.

D. Homophily Features

Homophily is the tendency of a user in the social network to associate or form a bond with similar others. [2] We used nine homophilic features to measure the similarity between the user and their friends. These homophilic features include (1) political, (2) education, (3) religious, (4) "interested in" (sexual preference according to Facebook), (5) hometown, (6) workplace, (7) profession, (8) user interests and (9) group membership similarity. Each of the following features corresponds to the TF-IDF cosine similarity of the relative description provided by the two friends on their profile. If the description included a link to another Facebook page, we included the text of this page as well. The reason to use these features was the assumption that a different degree of friendship has a different degree of similarities. From these features, we observed that there was a high degree of hometown similarity among all other similarities. Our dataset consists of people from Boise area so it was natural that they have higher hometown similarity. Out of four friend categories, casual friends had highest hometown similarity. We can infer that people tend to add friends on Facebook when they have similar hometown regardless of knowing them offline. This

[2]https://en.wikipedia.org/wiki/Homophily

also applied in the education and group similarities. Among the all, acquaintances had least similarity scores in most of the homophilic attributes. Moreover, we noted that there was fewer similarities in political view, religious view, profession, and groups among the user-friend pair in our dataset and it did not provide much significant information.

VI. Research Questions

In analyzing our friendship strength model, we address two important research questions.

[Q1] *Are interactions good estimator of friendship strength?*

The existing research [8], [5] has shown that interactions alone have the ability to detect strong friends and weak friends. However, since we believe that not all friends are equal and hence we want to see how these interaction variables treat to different classes of friend i.e. casual, acquaintance, good and close friends.

[Q2] *How do the sentiment-based features relate to the different friend categories?*

We believe that comment sentiments across the user and their friends could be a factor in determining the friendship strength. For example, close friends tend to use more emoticons than acquaintances or casual friends. There are words, which are specific to the close friends. Therefore, our goal here is to extend our first research question by evaluating the friendship strength based on user friend comments. We would be using sentiment analysis and other linguistic features to find the strength of comment. Using sentiment-based features to discuss the friendship strength is our novelty.

VII. Experiments

We implemented the proposed features and tested their accuracy in the prediction task with 10-fold cross validation by using different classification algorithms, namely logistic regression, support vector machine, and random forest[3]. To deal with class unbalance, we used stratified random sampling to select the train-test pairs and class weighting to learn the model.

We tested all the proposed features on the four-class classification task. Unfortunately, we did not obtain the desirable results. The proposed features perform with an accuracy of 0.46 with random forest (best performing classifiers) on our dataset. However, manual evaluation of the four classes suggests that close and good are near to each other while acquaintances and casual have similarities. In addition, the analysis of the false positives between the close/good vs. acquaintances/casual showed that there were many close and good friend pairs incorrectly classified as acquaintances. The reason behind this is zero reactions and zero mutual friends. Although it is highly likely that close friends do not interact much with social media, but since we are considering interactions for most of our features, we selected the ones having likes and mutual friends greater than zero. In addition, it is a general observation that close friends privately chat in social media. Since we do not have private chat messages, we would like to remove these zero interactions. In addition, since we are using comments as our major source of the feature, we are considering removing the user friend pairs whose total comment length is less than 50. We, however, keep the ones with the closeness signifying words.

Therefore, we are focusing on the following four binary classification problems in the rest of the paper:

1) Close and Good vs. Acquaintances and Causal (CL+GO vs. CA+AC);
2) Close, Good, and Causal vs. Acquaintances (CL+GO+CA vs. AC);
3) Close vs. Acquaintance (CL vs. AC);
4) Close vs. Acquaintance and Casual (CL vs. AC+CA).

Table I (1^{st} row) reports precision, recall, accuracy, and AUROC for all the above classification problems for the best performing classifier (random forest) and all the 23 features proposed in the paper. These features perform pretty well in classifying Close, Good, and Causal vs. Acquaintances (accuracy of 0.79 and AUROC of 0.80) and Close vs. Acquaintance (accuracy of 0.82 and AUROC of 0.83). We obtain 0.73 in both accuracy and AUROC in classifying Close and Good vs. Acquaintances and Causal and 0.75 in both accuracy and AUROC in classifying Close vs. Acquaintance and Casual.

We compared our result with a baseline given by the Bag of Words Model (BoWM) on the set of all comments shared between a friend pair. As shown in Table I, our model significantly improves over the baseline, which is able to get an accuracy between 0.59 and 0.64, and an AUROC between 0.59 and 0.63 across all classification problems.

Finally, the combination of our 23 features and BoWM does not improve either the accuracy or the AUROC of our features.

A. Feature Selection

Next, we performed feature selection to have a better understanding of our features and their relationship with the class variable, and to reduce misclassification. We used three different techniques for feature selection, namely Pearson Correlation Coefficient, Recursive Feature Elimination, and Ensemble of Decision Trees for Feature Importance. For each technique, we selected the most important features for each of the four binary classification problems considered in the paper.

1) Pearson Correlation Coefficient (PCC): This is a univariate feature selection method which examines the relationship between each individual feature and the class variable. The resulting value of the coefficient lies between [-1, 1], where -1 means perfect negative correlation while +1 means perfect positive correlation. We selected as most important features the set of features having an absolute value of PCC greater than 0.10 for at least one classification problem. The resulting set of features is: *average comment length, comment polarity, contradiction rank, agreement rank, reaction score for likes, loves, haha, and sad, friend tag score, Jaccard similarity, and closeness variable*.

[3]Due to the lack of space, we report in the paper the results for the best classifier only.

Model	Precision				Recall				Accuracy				AUROC			
	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
All Features	**0.76**	0.80	0.86	0.76	0.69	0.80	0.82	0.73	0.73	0.79	0.82	0.75	0.73	0.80	0.83	0.75
BoWM of comments	0.57	0.59	0.63	0.61	**0.72**	**0.81**	**0.88**	0.72	0.59	0.62	0.64	0.62	0.59	0.62	0.62	0.63
All Features + BoWM	0.74	0.80	0.80	0.74	0.70	0.80	0.87	0.73	0.73	0.79	0.81	0.73	0.73	0.79	0.80	0.73
Feature Subset 1 (FS1)	0.74	0.83	**0.87**	0.78	0.69	0.79	0.86	0.74	0.72	**0.82**	**0.85**	0.76	0.73	**0.82**	**0.85**	0.75
Feature Subset 2 (FS2)	0.73	0.83	0.86	0.78	0.69	0.75	0.82	**0.75**	0.72	0.78	0.82	**0.77**	0.72	0.79	0.83	**0.77**
Feature Subset 3 (FS3)	**0.76**	0.82	0.78	**0.79**	**0.72**	0.72	0.81	0.73	**0.75**	0.77	0.77	0.76	**0.74**	0.77	0.77	0.76
Feature Subset 4 (FS4)	**0.76**	**0.85**	0.86	0.77	0.70	0.72	0.83	0.74	0.73	0.80	0.83	0.76	0.73	0.81	0.82	0.76
Sentiment Features only	0.57	0.70	0.64	0.63	0.59	0.60	0.70	0.66	0.57	0.65	0.62	0.63	0.58	0.65	0.62	0.64

TABLE I: Performance comparison for different models on our four classification problems. 1: CL+GO vs. CA+AC, 2: CL+GO+CA vs. AC, 3: CL vs. AC, 4: CL vs. AC+CA

2) Recursive Feature Elimination (RFE): This method recursively removes attributes and builds a model based on those attributes that remain. We have used logistic regression with this model and used model accuracy to identify attributes or combination of attributes, which contribute the most in predicting the class. According to this technique, the top five features are: (1) *Average Comment length, reaction score for loves, friend tag score, Jaccard similarity*, (2) *closeness variable*, (3) *contradiction rank*, (4) *user interests similarity*, (5) *reaction score for sad*.

3) Ensemble of Decision Trees for Feature Importance: This method utilizes an ensemble of Extra Trees classifiers to compute the relative importance of each feature. The relative importance (for the classification task) of a feature f in a set of features is given by the depth of f when it is used as a decision node in a tree. According to this method, the top six features are: (i) *reaction score for likes*, (ii) *friend tag score*, (iii) *Jaccard similarity*, (iv) *user interests similarity*, (v) *average comment length*, and (vi) *contradiction rank*.

Thus, based upon the union of features extracted according to the above feature selection methods, we filtered out different feature subsets and checked them for classification improvement. The best performing feature subsets are:

Feature Subset 1 (FS1): average comment length, likes, loves, friend posts, mutual friends, and closeness variable.

Feature Subset 2 (FS2): average comment length, contradiction Rank, likes, friend posts, mutual friends, and interests similarity.

Feature Subset 3 (FS3): average comment length, contradiction rank, likes, sad, friend posts, mutual friends, and interests similarity.

Feature Subset 4 (FS4): average comment length, contradiction rank, likes, loves, friend posts, mutual friends, interest similarity and closeness variable.

The second set of rows in Table I shows the performances of the above subset of features on the four binary classification problems. Best performances are obtained with random forest in all these cases as well. Generally, these subsets of features allow improving the results obtained with the complete set of features.

Close and Good vs. Acquaintances and Causal: For this classification problem, the model built from feature subset 3 performs best with a precision of 0.76, recall of 0.70, accuracy of 0.74, AUROC of 0.74. Feature subset 3 contains most of the features from the feature selection process using RFE. Feature subsets 1, 2, and 4 performed slightly worse for this problem.

Close, Good and Causal vs. Acquaintances: In this case, feature subsets 1 and 4 performed pretty well. The model built on feature subset 1 performed the best with a precision of 0.83, recall of 0.79, accuracy of 0.82, and AUROC of 0.82. The model containing feature subset 4 performed equally well with the precision of 0.85, recall of 0.72, accuracy of 0.80, and AUROC of 0.81.

Close vs. Acquaintances: Feature subsets 1 outperforms all the other sets of features for this classification problem. It achieves an accuracy of 0.85 and an AUROC of 0.85. Precision and recall are 0.87 and 0.86, respectively.

Close vs. Acquaintances and Causal: In this classification problem, feature subset 2 performs the best with a precision of 0.78, recall of 0.75, accuracy of 0.77, AUROC of 0.77.

B. Interaction Features Only

In this experiment, we see the importance of interaction features only in predicting the friendship strength. Upon taking general interaction features only from best performing models for all four datasets, we see that general interaction features alone have a very good capability of determining the friendship strength. Table II shows the area under ROC value for all four different datasets using their best features. Along datasets CL+GO+CA vs. AC, CL vs. AC, CL vs. AC+CA, we get ROC of 0.80, 0.74 and 0.70 respectively. As we can see, interaction features alone were not the deciding features in classifying the dataset combinations, CL+GO vs. CA+AC. However, getting an area under the ROC curve more than 0.63 signifies that interaction features played its positive part in determining friendship strength across these datasets as well. Since close, good and casual have similar interactions in the dataset, performing prediction by separating these classes with interaction features may not have helped much.

This experiment answers our research question **Q1**, that interaction based features are good estimators of friendship strength across different friend categories.

C. Contribution of Sentiment-based Features

We also wanted to see if sentiment-based features play important role in determining the friendship strength to answer our research question **Q2**. First of all, we observe that the model containing only sentiment-based features has poor accuracy and AUROC (see last row in Table I). However, we compared the classification results with and without sentiment-based features to identify the strength of these features. Like the experiment on interaction features only, we take the best results obtained from all four classification tasks. Table II (4^{th} column) shows that in most of the classification problems, the performance of the classifiers decreases as we remove the sentiment-based features from the model. However, the AUROC for Close vs. Acquaintance and Casual does not show any change in the performance after removal of sentiment-based features. Here other features played important role in predictability.

Generally, sentiment-based features help in improving the classification performances. Sentiment-based features like contradiction rank and closeness variable contributed to our best performing models. Our assumption that good friends contradict less than acquaintances worked here. In addition, our assumption that good friends use more closeness related words worked as well.

D. Comparison with Results from Related Work

We obtained an accuracy of 0.85 and an AUROC of 0.85 in classifying close vs. acquaintance friends. We achieved the same accuracy result obtained by Gilbert et al. [4] with 70 features but by using a smaller set of 6 features.

Jones et al. [5] obtained a comparable accuracy of 0.86 and an AUROC of 0.92 in discriminating real life closest friends from non-closest friends. They pointed out *media multiplexity* as the primary reason for their success. Media multiplexity assumes that if two people interact in one social media then they interact equally well in another medium (e.g. email, phone, instant messaging and in-person contact). We did not see much media multiplexity in our dataset. There were close friends in real life without any interactions in Facebook while there were casual and acquaintances friends having a large number of interactions. In addition, they have used private Facebook messages sent between the user-friend pair as one of the features. We do not have this data and we cannot test how much is the contribution of this feature in the overall predictive power.

VIII. Conclusions

In this paper, we developed a friendship strength model to evaluate the strength of friendship in social media by utilizing interaction, structural, homophily, and sentiment-based features. This model has applications in privacy preserving on social media. We have obtained an AUROC of 0.85 in successfully identifying close friends vs. acquaintances and an AUROC of 0.82 in distinguishing acquaintances from the other three categories of friendship, by using selected subsets of our features. Our experiments clearly depict that features like average comment length, reaction scores for likes and love, friend tag score, Jaccard similarity, and closeness variable had a positive correlation with friendship strength. Our experiments also show that sentiment-based features helped to improve the performance of the model.

Classification Task and Best Model	AUROC	AUROC (Interaction Features only)	AUROC (w/o Sentiment based Features)
CL+GO vs. CA+AC (FS3)	0.74	0.63	0.72
CL+GO+CA vs. AC (FS1)	0.82	0.80	0.78
CL vs. AC (FS1)	0.85	0.74	0.84
CL vs. AC+CA (FS2)	0.77	0.70	0.77

TABLE II: AUROC for best performing models, AUROC with interaction features only, and AUROC without sentiment-based features.

References

[1] M. I. Akbas, R. N. Avula, M. A. Bassiouni, and D. Turgut, "Social network generation and friend ranking based on mobile phone data," in *ICC*, 2013.

[2] S. Kumar, F. Spezzano, V. S. Subrahmanian, and C. Faloutsos, "Edge weight prediction in weighted signed networks," in *ICDM*, 2016, pp. 221–230.

[3] C. K.-S. Leung and S. K. Tanbeer, "Mining social networks for significant friend groups," in *DASFAA Workshops*, 2012.

[4] E. Gilbert and K. Karahalios, "Predicting tie strength with social media," in *SIGCHI*, 2009.

[5] J. J. Jones, J. E. Settle, R. M. Bond, C. J. Fariss, C. Marlow, and J. H. Fowler, "Inferring tie strength from online directed behavior," *PloS one*, vol. 8, no. 1, 2013.

[6] S. G. Roberts, "Constraints on social networks," *Social Brain, Distributed Mind, Proceedings of the British Academy*, 2010.

[7] R. A. Hill and R. I. Dunbar, "Social network size in humans," *Human nature*, vol. 14, no. 1, 2003.

[8] R. Xiang, J. Neville, and M. Rogati, "Modeling relationship strength in online social networks," in *WWW*, 2010.

[9] W. Sherchan, S. Nepal, and C. Paris, "A survey of trust in social networks," *ACM Computing Surveys (CSUR)*, vol. 45, no. 4, 2013.

[10] S. K. Tanbeer, C. K. Leung, and J. J. Cameron, "Difson: discovering influential friends from social networks," in *CASoN*, 2012.

[11] J.-P. Onnela, J. Saramäki, J. Hyvönen, G. Szabó, D. Lazer, K. Kaski, J. Kertész, and A.-L. Barabási, "Structure and tie strengths in mobile communication networks," *Proceedings of the National Academy of Sciences*, vol. 104, no. 18, 2007.

[12] H. Zhang and R. Dantu, "Predicting social ties in mobile phone networks," in *IEEE ISI*, 2010.

[13] N. K. Baym and A. Ledbetter, "Tunes that bind? predicting friendship strength in a music-based social network," *Information, Communication & Society*, vol. 12, no. 3, 2009.

[14] M. Granovetter, "The strength of weak ties: A network theory revisited," *Sociological theory*, 1983.

[15] H. Kashima and N. Abe, "A parameterized probabilistic model of network evolution for supervised link prediction," in *ICDM*, 2006.

[16] R. West, H. S. Paskov, J. Leskovec, and C. Potts, "Exploiting social network structure for person-to-person sentiment analysis," *Transactions of the Association for Computational Linguistics*, vol. 2, 2014.

[17] J. P. Dickerson, V. Kagan, and V. Subrahmanian, "Using sentiment to detect bots on twitter: Are humans more opinionated than bots?" in *ASONAM*, 2014.

[18] J. J. Cameron, C. K.-S. Leung, and S. K. Tanbeer, "Finding strong groups of friends among friends in social networks," in *DASC*, 2011.

[19] F. Jiang, C. K.-S. Leung, and S. K. Tanbeer, "Finding popular friends in social networks," in *CGC*, 2012.

[20] S. K. Tanbeer, F. Jiang, C. K.-S. Leung, R. K. MacKinnon, and I. J. Medina, "Finding groups of friends who are significant across multiple domains in social networks," in *CASoN*, 2013.

[21] V. Arnaboldi, A. Guazzini, and A. Passarella, "Egocentric online social networks: Analysis of key features and prediction of tie strength in facebook," *Computer Communications*, vol. 36, no. 10, 2013.

[22] J. Golbeck, "Generating predictive movie recommendations from trust in social networks," in *IFIPTM*, 2006.

[23] I. Alsmadi, D. Xu, and J.-H. Cho, "Interaction-based reputation model in online social networks," in *ICISSP*, 2016.

[24] J.-H. Cho, I. Alsmadi, and D. Xu, "Privacy and social capital in online social networks," in *GLOBECOM*, 2016.

[25] C. J. Hutto and E. Gilbert, "Vader: A parsimonious rule-based model for sentiment analysis of social media text," in *ICWSM*, 2014.