SHINE: Signed Heterogeneous Information Network Embedding for Sentiment Link Prediction

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将括号中的文字作为注释放在页脚处，红字仅作为提示，不需要输入(∗This work is done while H. Wang and M. Hou are visiting Microsoft Research Asia. †M. Guo is the corresponding author.)

ABSTRACT

In online social networks people often express attitudes towards others, which forms massive sentiment links among users. Predicting the sign of sentiment links is a fundamental task in many areas such as personal advertising and public opinion analysis. Previous works mainly focus on textual sentiment classification, however, text information can only disclose the “tip of the iceberg” about users’ true opinions, of which the most are unobserved but implied by other sources of information such as social relation and users’ profile. To address this problem, in this paper we investigate how to predict possibly existing sentiment links in the presence of heterogeneous information. First, due to the lack of explicit sentiment links in mainstream social networks, we establish a labeled heterogeneous sentiment dataset which consists of users’ sentiment relation, social relation and profile knowledge by entity-level sentiment extraction method. Then we propose a novel and flexible end-to-end Signed Heterogeneous Information Network Embedding (SHINE) framework to extract users’ latent representations from heterogeneous networks and predict the sign of unobserved sentiment links. SHINE utilizes multiple deep autoencoders to map each user into a low-dimension feature space while preserving the network structure. We demonstrate the superiority of SHINE over state-of-the-art baselines on link prediction and node recommendation in two real-world datasets. The experimental results also prove the efficacy of SHINE in cold start scenario.

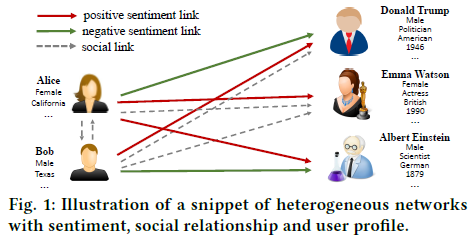
1 INTRODUCTION

The past decade has witnessed the proliferation of online social networks such as Facebook, Twitter and Weibo. In these social network sites, people often share feelings and express attitudes towards others, e.g., friends, movie stars or politicians, which forms sentiment links among these users. Different from explicit social links indicating friend or follow relationship, sentiment links are implied by the semantic content posted by users, and involve dif-ferent types: positive sentiment links express like, trust or support attitudes, while negative sentiment links signify dislike or disap-proval of others. For example, a tweet saying “Vote Trump!” shows a positive sentiment link from the poster to Donald Trump, and “Trump is mad...” indicates the opposite case.

For a given sentiment link, we define its sign to be positive or negative depending on whether its related content expresses a positive or negative attitude from the generator of the link to the recipient [14], and all such sentiment links form a new net-work topology called sentiment network. Previous work [6, 11, 15] mainly focuses on sentiment classification based on the concrete content posted by users. However, they cannot detect the existence of sentiment links without any prior content information, which greatly limits the number of possible sentiment links that could be found. For example, if a user does not post any word concerning Trump, it is impossible for traditional sentiment classifiers to ex-tract the user’s attitude towards him because “one cannot make bricks without straw”. Therefore, a fundamental question is, can we predict the sign of a given sentiment link without observing its related content? The solution to this problem will benefit a great many online services such as personalized advertising, new friends recommendation, public opinion analysis, opinion polls, etc.

Despite the great importance, there is little prior work concern-ing predicting the sign of sentiment links among users in social networks. The challenges are two-fold. On the one hand, lack of explicit sentiment labels makes it difficult to determine the polarity of existing and potential sentiment links. On the other hand, the complexity of sentiment generation and the sparsity of sentiment links make it hard for algorithms to achieve desirable performance. Recently, several studies [12, 14, 31, 35] propose methods to solve the problem of predicting signed links. However, they rely heavily on manually designed features and cannot work well in real-world scenarios. Another promising approach called network embedding [8, 17, 23, 26], which automatically learns features of users in net-work, seems plausible to solve the task. However, they can only apply to networks with positive-weighted (i.e., unsigned) and single-type (i.e., homogeneous) edges, which limits their power in the task of practical sentiment link prediction.

Based on the above facts, in this paper we investigate the prob-lem of predicting sentiment links in absence of sentiment related content in online social networks. Our work is two-step. First, con-sidering the lack of labeled data, we establish a labeled sentiment dataset from Weibo, one of the most popular social network sites in China. We leverage state-of-the-art entity-level sentiment extrac-tion method to calculate the sentiment of the poster towards the celebrity in each tweet. Besides, to handle the sparsity problem, we collect two additional types of side information: social relationship among users and profile knowledge of users and celebrities. Our choices are enlightened by [27] and [34], respectively, in which [27] demonstrates that the structural information of social net-works can greatly affect users’ preference towards online items, and [34] proves that information from knowledge base could boost the performance of recommendation. The heterogeneous informa-tion networks are illustrated in Fig. 1.



To explore more possible sentiment links from the network, in the second step, we propose a novel end-to-end framework termed as Signed Heterogeneous Information Network Embedding (SHINE). Greatly different from existing network embedding approaches, SHINE is able to learn user representation and predict sentiment from signed heterogeneous networks. Specifically, SHINE adopts multiple deep autoencoders [20], a type of deep-learning-based embedding technique, to extract users’ highly nonlinear represen-tations from the sentiment network, social network and profile network, respectively. The learned three types of user represen-tations are subsequently fused together by specific aggregation function for further sentiment prediction. In addition to the adapt-ability to signed heterogeneous networks, the superiority of SHINE also lies in its end-to-end prediction technology and high flexibil-ity of adding or removing modules of side information (i.e., social relationship and profile knowledge), which is discuss in Section 5.

We conduct extensive experiments on two real-world datasets. The results show that SHINE achieves substantial gains compared with baselines. Specifically, SHINE outperforms other strong base-lines by 8.8% to 16.8% in the task of link prediction on Accuracy, and by 17.2% to 219.4% in the task of node recommendation on Recall@100 for positive nodes. The results also prove that SHINE is able to utilize the side information efficiently, and maintains a decent performance in cold start scenario.

2 RELATED WORK

2.1 Signed Link Prediction

Our problem of predicting positive and negative sentiment links connects to a large body of work on signed social networks, in-cluding trust propagation [9], spectral analysis [13], and social me-dia mining [22]. For the link prediction problem in signed graphs, Leskovec. et al. [14] adopt signed triads as features for prediction based on structural balance theory. Ye et al. [31] utilize transfer learning to leverage edge sign information from source network and improve prediction accuracy in target network. Tang et al. de-sign NeLP framework [21] which exploits positive links in social media to predict negative links. The difference between the above work and ours is that we construct a labeled dataset by entity-level sentiment extraction method, as there is no explicit signed links in mainstream online social networks. Besides, we use state-of-the-art deep learning approach to learn the representation of links.

2.2 Network Embedding

There is a long history of work on network embedding. Earlier works such as IsoMap [24] and Laplacian Eigenmap [1] first con-struct the affinity graph of data using the feature vectors and then embed the affinity graph into a low-dimension space. Recently, DeepWalk [17] deploys random walk to learning representations of social network. LINE [23] proposes objective functions that pre-serve both local and global network structures for network embed-ding. Node2vec [8] designs a biased random walk procedure to learn a mapping of nodes that maximizes the likelihood of preserving network neighborhoods of nodes. SDNE [26] uses autoencoder to capture first-order and second-order network structures and learn user representation. However, these methods can only address un-signed and homogeneous networks. Additionally, several studies focus on representation learning in the scenario of heterogeneous network [3, 32], attributed network [10], or signed network [29, 33]. However, these methods are specialized in only one particular type of networks, which is not applicable to the problem of sentiment prediction in real-world signed and heterogeneous networks.

3 DATASET ESTABLISHMENT

In this section we introduce the process of collecting data from online social networks, and discuss the details of how to extract sentiment towards celebrities from tweets.

3.1 Data Collection

3.1.1 Weibo Tweets. We select Weibo1 as the online social net-works studied in this work. Weibo is one of the most popular social network sites in China which is akin to a hybrid of Facebook and Twitter. We collected 2.99 billion tweets on Weibo from August 14, 2009 to May 23, 2014 as raw dataset. To filter out useful data which contains sentiment towards celebrities, we first apply Jieba2, the most popular Chinese text segmentation tool, to tag the part of speech (POS) of each word for each tweet. Then we select those tweets containing words with POS tagging as “person name” which exist in our established celebrity database (detailed in Section 3.1.4).

After getting the set of candidate tweets, for each tweet we calculate its sentiment value (-1 to +1) towards the mentioned celebrities, and select those tweets with high absolute sentiment values. The final dataset consists of a set of triples (a, b, s), where a is the user who posts the tweet, b is the certain celebrity mentioned in the tweet, and s ∈ {+1, −1} is the sentiment polarity of user a towards user b. The method of calculating sentiment values is detailed in Section 3.2.

3.1.2 Social Relation. In addition to the sentiment dataset, we also collect the social relation among users from Weibo. The dataset of social relation consists of tuples (a, b), where a is the follower and b is the followee.

3.1.3 Profile of Ordinary Users. The profile of ordinary users are collected from Weibo. For each ordinary user, we extract two of his attributes, gender and location, as his profile information. The attribute values are represented as one-hot vectors.

3.1.4 Profile of Celebrities. We use Microsoft Satori3 knowledge base to extract profile of celebrities. First, we traverse the knowledge base and select terms with object type as “person”. Then we filter out popular celebrities with high edit frequency in knowledge base and high appearance frequency in Weibo tweets. For each of these “hot” celebrities, we extract 9 attributes as his profile information: place of birth, date of birth, ethnicity, nationality, specialization, gen-der, height, weight, and astrological sign. Values of these attributes are discretized so that every celebrity’s attribute values can be ex-pressed as one-hot vectors. Furthermore, we remove celebrities with ambiguous names as well as other noises.

3.2 Sentiment Extraction

To extract users’ sentiment towards celebrities in tweets, we first generate a sentiment lexicon consisting of words and their sentiment orientation (SO) scores. To achieve this, we manually construct a emoticon-sentiment mapping file and map each tweet to positive or negative class according to the label of emoticon appeared in the tweet. For example, “I love Kobe! [kiss]” is mapped to positive class if the key-value pair ([kiss], positive) exists in the emoticon-sentiment mapping file. Note that the class of emoticon cannot be directly regarded as the sentiment towards celebrities since we found a large number of mismatch cases, e.g., “Miss you Taylor Swift [cry][cry]”. Afterwards, for each word (segmented by Jieba) with occurrence frequency from 2,000 to 10,000,000 in the raw tweets datasets, similar to [2], we calculate its SO score as



where PMI is the point-wise mutual information [25] defined as

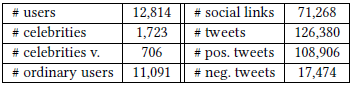


pos and neg are the tweets of positive and negative class, respectively. SO scores are subsequently normalized to [−1, 1].

After getting the lexicon, we use SentiCircle [19] to calculate sentiment towards celebrities in each tweet. Given a piece of tweet as well as the mentioned celebrity, we represent the contextual semantics of the celebrity as a polar coordinate space, where the celebrity is situated in the origin and other terms in the tweet are scattered around. Specifically, for celebrity term c, the coordinate of term ti is (ri , θi ), where ri is the inverse of distance between c and ti in syntax dependence graph generated by LTP [4], and θi = SO(ti ) · π . The overall sentiment towards the celebrity c is, therefore, approximated as the geometric center of all terms ci . We take the projection of the geometric center on y-axis as final sentiment value towards the celebrity.

To validate the effectiveness of sentiment extraction, we ran-domly select 1,000 tweets (500 positive and 500 negative tagged by our method) in Weibo sentiment dataset, and manually label each one of them. The result shows that the precision is 95.2% for positive class and 91.0% for negative class, which we believe is accurate enough for subsequent experiments. The basic statistics of Weibo sentiment datasets is presented in Table 1.

Table 1: Statistics of Weibo sentiment datasets. “celebrities v.” means the celebrities owning verified accounts on Weibo.



**涉及到的考点：**

1. **插入图片、图表、公式**
2. **大小标题**
3. **页脚的引用**
4. **超链接**
5. **段落格式**