Modeling Mutual Influence Between Social Actions and Social Ties

Xiaofeng Yu, Jun Qing Xie

HP Laboratories
HPL-2014-18

Keyword(s):
Social Actions and Social Ties; Mutual Influence

Abstract:
In online social media, social action prediction and social tie discovery are two fundamental tasks for social network analysis. Traditionally, they were considered as separate tasks and solved independently. In this paper, we investigate the high correlation and mutual influence between social actions (i.e. user-behavior interactions) and social ties (i.e. user-user connections). We propose a unified coherent framework, namely mutual latent random graphs (MLRGs), to flexibly encode evidences from both social actions and social ties. We introduce latent, or hidden factors and coupled models with users, users' behaviors and users' relations to exploit mutual influence and mutual benefits between social actions and social ties. We propose a gradient based optimization algorithm to efficiently learn the model parameters. Experimental results show the validity and competitiveness of our model, compared to several state-of-the-art alternative models.
Modeling Mutual Influence Between Social Actions and Social Ties

Abstract

In online social media, social action prediction and social tie discovery are two fundamental tasks for social network analysis. Traditionally, they were considered as separate tasks and solved independently. In this paper, we investigate the high correlation and mutual influence between social actions (i.e. user-behavior interactions) and social ties (i.e. user-user connections). We propose a unified coherent framework, namely mutual latent random graphs (MLRGs), to flexibly encode evidences from both social actions and social ties. We introduce latent, or hidden factors and coupled models with users, users’ behaviors and users’ relations to exploit mutual influence and mutual benefits between social actions and social ties. We propose a gradient based optimization algorithm to efficiently learn the model parameters. Experimental results show the validity and competitiveness of our model, compared to several state-of-the-art alternative models.

1 Introduction

With the dramatically rapid growth and great success of many large-scale online social networking services, social media bridge our daily physical life and the virtual Web space. Popular social media sites (e.g., Facebook and Twitter) and mobile social networks (e.g., Foursquare) have gathered billions of acting users and are still attracting millions of newbies everyday. Modeling social actions and social ties are two fundamental tasks in online social media. Social actions are the users’ activities or behaviors in socially connected networks. For example, a social action can be “posting a tweet” on Twitter or the “check-in” behavior on Foursquare. A social tie or social relation is referred to any relationship between two or more individual users in a social network, such as the friend and colleague relationships. By understanding a user’s behaviors and accordingly exploiting potentially interesting services to her/him, one can improve the user’s experience and boost the revenue of social media sites. Also, precise social tie prediction will help people tap into the wisdom of crowds, to aid in making more informed decisions.

Since individual users are socially connected, social influence occurs through information diffusion in social networks. Social influence happens when one’s opinions or behaviors are affected by others. It is well known that different types of social ties have essentially different influence on social actions. Intuitively, a user’s trusted friends on the web affect that user’s online behavior. Ma et al. (2009) and Ma et al. (2011) claimed that one user’s final behavior decision is the balance between his/her own taste and her/his trusted friends’ favors. On the other hand, social actions also have important influence on social ties. Obviously, users with similar preferences or behaviors are more likely to be friends than others in social media. Users with momentous activities will attract many other users to be connected with. On the contrary, no body will be interested in users with trivial or insignificant behaviors.

Consequently, we face some very interesting questions: Is there any dynamics or mutual influence between social actions and social ties? To what extent do they influence each other? A fundamental mechanism that drives the dynamics of networks is the underlying social phenomenon of homophily (McPherson et al., 2001): people tend to follow the behaviors of their friends, and people tend to create relationships with other people who are already similar to them. This suggests that both actions and ties are bi-directionally correlated and mutually influenced in social media, they could be mutually reinforced if modeled jointly.
Inspired by this mechanism, we propose a single unified framework based on exponential-family random graph models \cite{Frank and Strauss, 1986, Wasserman and Pattison, 1996} to exploit homophily for simultaneous social action prediction and social tie discovery. This mutual latent random graph (MLRG) framework incorporates shared latent factors with users, users’ behaviors and users’ relations, and defines coupled models to encode both social action and social tie information, to capture dynamics and mutual influence between them. We propose a gradient based algorithm for learning and optimization. During the learning procedure, social actions (i.e. user-behavior interactions), social ties (i.e. user-user connections), and deep dependencies and interactions between them could be efficiently explored. Experimental results demonstrate that social actions and social ties are highly correlated and mutually helpful. By coupling actions with ties jointly in a single coherent framework, MLRG achieves significantly better performance on both social action prediction and social tie inference, compared to state-of-the-art systems modeling them independently.

2 Related Work

Social network analysis has attracted much interest in both academia and industry recently. Considerable research and engineering has been conducted for social media modeling, analytics and optimization, including social community detection \cite{Fortunato, 2010}, user behavior modeling and prediction \cite{Ben, evenuto et al., 2009, Kwak et al., 2010, Ma et al., 2009, Ma et al., 2011}, social tie analysis \cite{Tang et al., 2011, Tang et al., 2012}, social sentiment analysis \cite{Wasserman et al., 1994, Pang and Lee, 2008}, etc.

Social action investigation is essentially important in online social media. Users behaviors could be affected by various kinds of factors, such as users’ attributes, users’ historical behaviors, social influence and social network structures. Based on this motivation, \textit{Tan et al.} \cite{2010} proposed a noise tolerant time-varying model to track social actions. Aiming at modeling user actions more accurately and realistically, \textit{Ma et al.} \cite{2009} and \textit{Ma et al.} \cite{2011} considered connections among users and proposed social trust ensemble to fuse the users’ tastes and their trusted friends’ favors together. \textit{Gao et al.} \cite{2013} investigated users’ social behaviors from a spatio-temporal-social aspect in location-based mobile social networks.

Social tie is the most basic unit to form the network structure. \textit{Tang et al.} \cite{2011} proposed a partially labeled factor graph model to infer the type of social relationships. \textit{Tang et al.} \cite{2012} further incorporate social theories, including social balance, social status, structural hole, and two-step flow theories and leverage features defined based on those social theories to infer social ties across heterogeneous networks. As can be seen, social actions and social ties were modeled as separate and independent tasks in the above-mentioned approaches, deep interactions and mutual influence between them were not taken into consideration. According to the homophily phenomenon, exploring bi-directional information and mutual influence between them is intuitively appealing.

We are also aware of several research work attempting to explore joint models to capture mutual benefits and deep dependencies between different tasks in NLP, data mining and information extraction research communities. \textit{Ko et al.} \cite{2007} proposed a joint answer ranking framework based on probabilistic graphical models for question answering. \textit{Liu et al.} \cite{2009} developed a Bayesian hierarchical approach, the topic-link LDA, to perform topic modeling and author community discovery for large-scale linked documents in one unified framework. \textit{Zeng et al.} \cite{2013} presented a semi-supervised graph-based approach to joint Chinese word segmentation and POS tagging. However, none of these models has been investigated or applied to social media and social network analysis. Currently, research on building joint approaches is still in the infancy stage. To the best of our knowledge, there is few systematically study on building joint models to explore mutual influence for social actions and social ties.

3 Model

In this section we consider both social action prediction and social tie inference in the context of social media, where evidences for both actions and ties are available. We begin by necessary description of preliminaries and notations, we then present the mutual latent random graphs (MLRGs) model, upon which both sources of evidence could be exploited simultaneously to capture their mutual influence. We
also discuss the major difference and superiority of this model against several alternative models.

### 3.1 Preliminaries and Notations

Let \( G = (V, E) \) be a social network graph, where \( V = \{v_1, v_2, \ldots, v_N\} \) is the set of \( |V| = N \) users and \( E = \{e_{11}, e_{12}, \ldots, e_{M}\} \subseteq V \times V \) is the set of \( |E| = M \) connections between users. Let \( y = \{y_1, y_2, \ldots, y_N\}(y_i \in \mathcal{Y}) \) be the set of actions associated with \( N \) users, and \( s = \{s_{11}, s_{12}, \ldots, s_{M}\}(s_{ij} \in \mathcal{S}) \) be the set of corresponding social tie labels associated with \( M \) connections. The connection \( e_{ij}(1 \leq i, j \leq N, i \neq j) \) between \( v_i \) and \( v_j \) might be directed or undirected. To be consistent, both \( s_{ij} \neq s_{ji} \) and \( s_{ji} = s_{ij} \) are valid settings. Given the observed social network data \( D \) constructing the graph \( G \), our goal is to simultaneously detect the most likely types of actions \( y^* \) and ties \( s^* \) such that both of them are optimized.

### 3.2 Modeling Social Actions

To characterize the user action \( y_i \), we assume that for the user \( v_i \) there exist observable attributes or properties \( m_i \), such as the user’s registered information and historical actions. Without loss of generality, we further assume that there exist some hidden, or latent properties \( x_{ij} \) for \( v_i \). These properties are implicit and cannot be observed directly, such as the influence from social ties. Consequently, we denote the observable factor \( \phi(y_i, v_i, m_i) \) for observable properties and latent factor \( \phi_h(y_i, s_{ij}, x_{ij}) \) for hidden properties, respectively. Given the graph \( G \), the probability distribution of \( y_i \) depends on both observable and latent factors as:

\[
P_{y_i|G} \sim \phi(y_i, v_i, m_i), \quad P_{y_i|G} \sim \phi_h(y_i, s_{ij}, x_{ij}), \quad P_{y_i|G} \sim \phi(y_i, v_i, m_i)\phi_h(y_i, s_{ij}, x_{ij}). \quad (1)
\]

This model integrates two types of factors for both observable and latent properties. It captures not only the user-behavior dependencies, but also the influence from social ties, for exploring social actions.

### 3.3 Modeling Social Ties

To characterize the social tie \( s_{ij} \) between user pair \( (v_i, v_j) \), we also assume that there exist observable properties \( w_{ij} \), such as the posterior probability of the social tie \( s_{ij} \) assigned to \( (v_i, v_j) \). We denote the observable factor \( \phi'(s_{ij}, v_i, v_j, w_{ij}) \) for \( w_{ij} \). Similarly, we further assume that there exist some latent properties to incorporate the social action influence on social ties. To be consistent, we still use the vector \( x_{ij} \) to represent the latent properties and the latent factor \( \phi_h(y_i, s_{ij}, x_{ij}) \) to capture the social action influence on social ties. Note that both \( x_{ij} \) and \( \phi_h(y_i, s_{ij}, x_{ij}) \) now play double duties in encoding social action dependency and social tie connection simultaneously. On the one hand, \( \phi_h(y_i, s_{ij}, x_{ij}) \) exploits influence from social ties for modeling social actions. On the other hand, this factor exploits influence from social actions for modeling social ties. By doing so, the latent factor \( \phi_h(y_i, s_{ij}, x_{ij}) \) is bi-directionally coupled, encoding both sources of evidence and exploring mutual influence and dynamics between social actions and social ties. Such mutual influence and dynamics are crucial and modeling...
shown in the above table can be rewritten as

\[
P(y_i | y_j) \sim \phi(y_i, y_j) \phi_h(y_i, s_{ij}, x_{ij})
\]

\[
P(s_{ij} | y_i) \sim \phi'(s_{ij}, v_i, v_j, w_{ij})
\]

\[
P(y_i, s_{ij} | y_j) \sim \phi(y_i, y_j, s_{ij}, x_{ij})
\]

\[
P(s_{ij} | y_i, y_j) \sim \phi'(s_{ij}, v_i, v_j, w_{ij}) \phi_h(y_i, s_{ij}, x_{ij}).
\]

### 3.4 Modeling Mutual Influence

The mutual correlation between social actions and social ties advocates joint modeling of both sources of evidence in a single unified framework. Based on the above descriptions, we define our mutual latent random graph (MLRG) based on exponential-family random graph models (ERGMs) (Frank and Strauss 1986, Wasserman and Pattison 1996), which have gained tremendous successes in social network analysis and have even become the current state-of-the-art (Robins et al. 2007). To design a concrete model, one needs to specify distributions for the dependencies for MLRGs. According to the celebrated Hammersley-Clifford theory, the joint conditional distribution \( P(y_i, s_{ij}) | G \) is factorized as a product of potential functions over all cliques in the graph \( G \) and we summarize the MLRG in the above table. In summary, our model consists of three factors: the factor \( \phi(y_i, v_i, m_i) \) measuring dependencies of the social action \( y_i \) conditioned on \( G \), the factor \( \phi'(s_{ij}, v_i, v_j, w_{ij}) \) measuring the social tie \( s_{ij} \) between two arbitrary users \( v_i \) and \( v_j \) in \( G \), and the latent factor \( \phi_h(y_i, s_{ij}, x_{ij}) \) exploiting mutual influence between the social action \( y_i \) and social tie \( s_{ij} \).

The three factors \( \phi(\cdot), \phi_h(\cdot) \), and \( \phi'(\cdot) \) can be instantiated in different ways. In this paper, each factor is defined as the exponential family of an inner product over sufficient statistics (feature functions) and corresponding parameters. Each factor is a clique template whose parameters are tied. More specifically, we define these factors as

\[
\phi(y_i, v_i, m_i) = \frac{1}{Z_{\alpha}} \exp\left\{ \sum_{y_i \in Y} \alpha f(y_i, v_i, m_i) \right\}, \quad \phi_h(y_i, s_{ij}, x_{ij}) = \frac{1}{Z_{\beta}} \exp\left\{ \sum_{y_i \in Y, s_{ij} \in S} \beta g(y_i, s_{ij}, x_{ij}) \right\},
\]

\[
\phi'(s_{ij}, v_i, v_j, w_{ij}) = \frac{1}{Z_{\gamma}} \exp\left\{ \sum_{s_{ij} \in S} \gamma h(s_{ij}, v_i, v_j, w_{ij}) \right\},
\]

where \( \alpha, \beta, \) and \( \gamma \) are real-valued weighting vectors and \( f(\cdot), g(\cdot), \) and \( h(\cdot) \) are corresponding vectors of feature functions.

We denote \( \Theta = \{\alpha, \beta, \gamma\} \) as the set of model’s parameters, and concatenate all factor functions as \( \Theta_q(y_i, s_{ij}) = \alpha f(y_i, v_i, m_i) + \beta g(y_i, s_{ij}, x_{ij}) + \gamma h(s_{ij}, v_i, v_j, w_{ij}) \), the joint probability distribution shown in the above table can be rewritten as

\[
P(y_i, s_{ij} | G) = \prod_{y_i \in Y, s_{ij} \in S} \Phi(y_i, s_{ij}) = \frac{1}{Z} \exp\left\{ \sum_{y_i \in Y, s_{ij} \in S} \Theta_q(y_i, s_{ij}) \right\},
\]

where \( Z = Z_{\alpha} Z_{\beta} Z_{\gamma} \) is the partition function of our MLRG model.

Figure 3 shows an example social network \( V = \{v_1, v_2, v_3, v_4, v_5, v_6\}, Y = \{active, idle\}, S = \{friend, colleague, family\} \) and the corresponding 3D graphical representation of the MLRG model. The functions \( f(\cdot) \) model dependencies of social actions in the bottom part, and the functions \( h(\cdot) \) model dependencies of social ties in the upper part. More importantly, the functions \( g(\cdot) \) capture mutual influence and dependencies between social actions and social ties. As we will see, this modeling offers a natural formalism for exploiting bi-directional dependencies and interactions between social actions and social ties to capture their mutual influence, as well as a great flexibility to incorporate a large collection of arbitrary, overlapping and non-independent features.
3.5 Discussion

Noticably, our proposed MLRG model is essentially different from the standard exponential-family random graph models (ERGMs) and the prior models discussed in Section 3 mainly in two aspects. Firstly, compared to the standard ERGMs, the MLRG model defines latent factors to assume mutual and dynamical interaction between social ties and social actions. Secondly, compared to the prior models such as (Ma et al. 2009) and (Tang et al. 2010), MLRG provides a single unified framework to address both social action prediction and social tie inference simultaneously while enjoying the resources of both sources of evidence.

Importantly, we give an analytical explanation on the mutual nature of our model in terms of a random walk (Lovász 1996) perspective. A random walk on the graph $\mathcal{G}$ is a reversible Markov chain on the vertexes $V$. The social influence propagation procedure occurs through information diffusion in the social graph $\mathcal{G}$. More specifically, a user $v_i$ will propagate her/his influence to other related users, and will propagate more to the user which has a stronger relation (e.g., friendship) with $v_i$. The influence propagation will stop when the social graph reaches an equilibrium state, in which both social actions and social ties are mutually reinforced. Interestingly, this process is consistent with the homophily phenomenon that a user in the social network tends to be similar to their connected neighbors.

4 Learning and Inference

4.1 Mutual Optimization

The goal of learning MLRG model is to estimate a parameter configuration $\Theta = \{\alpha, \beta, \gamma\}$ such that the log-likelihood of observation is maximized. We define the log-likelihood objective function $\mathcal{O}(\Theta)$ of the observation given the graph $\mathcal{G}$ as

$$\mathcal{O}(\Theta) = \log P_{(y,s)|\mathcal{G}} - \log \Omega(\Theta) = \log[\exp\{\sum_{y_{ij} \in Y} \Theta q(y_{ij})\}] - \log Z - \log \Omega(\Theta), \tag{5}$$

where $\Omega(\Theta)$ is regularization to reduce over-fitting and a common choice is a spherical Gaussian prior with mean 0 and covariance $\delta^2 I$. $\Omega(\Theta) = \sum_{y_{ij} \in Y} \frac{\alpha^2}{2\sigma^2} + \sum_{y_{ij} \in Y, s_{ij} \in S} \frac{\beta^2}{2\sigma^2} + \sum_{s_{ij} \in S} \frac{\gamma^2}{2\sigma^2}$.

We propose a mutual gradient descent (MGD) algorithm based on the stochastic gradient descent (SGD) (Lecun et al. 1998, Bottou 2004) framework, for estimating the parameters efficiently in a mutual and collaborative manner. Once we have optimized the social action parameters $\alpha$ and $\beta$, the influence and hypotheses of social action can aid the learning of the social tie parameters $\gamma$ and $\alpha$, and vice versa. As shown in Algorithm 4, $\beta$ is coupled parameter vector for both actions and ties, and is updated twice in each iteration of MGD. By doing so, MGD not only allows learning of social action parameters to capture social tie influence, but it also optimizes social tie parameters to alleviate social action influence. This training procedure runs iteratively until convergence to boost both the optimization of social actions and social ties.

Each iteration of the MGD algorithm consists in drawing an example at random and applying parameter updates by moving in the direction defined by the stochastically approximated gradient of the loss function. This algorithm is computationally efficient, and convergence is very fast when the training examples are redundant since only a few examples are needed to perform. Furthermore, this algorithm is online and scale sub-linearly with the amount of training data, making it very attractive for large-scale datasets. We summarize the partial derivatives of the log-likelihood function $\mathcal{O}$ with respect to the parameter vectors $\alpha$, $\beta$ and $\gamma$ as follows:

$$\frac{\partial \mathcal{O}}{\partial \alpha} = \sum_{y_{ij} \in Y} f(y_{ij}, v_i, m_i) - \sum_{y_{ij} \in Y} f(y_{ij}, v_i, m_i) \times P_{(y,s)|\mathcal{G}} - \sum_{y_{ij} \in Y} \frac{\alpha^2}{2\sigma^2}, \tag{6}$$

$$\frac{\partial \mathcal{O}}{\partial \beta} = \sum_{y_{ij} \in Y, s_{ij} \in S} g(y_{ij}, s_{ij}, x_{ij}) - \sum_{y_{ij} \in Y, s_{ij} \in S} g(y_{ij}, s_{ij}, x_{ij}) \times P_{(y,s)|\mathcal{G}} - \sum_{y_{ij} \in Y, s_{ij} \in S} \frac{\beta^2}{2\sigma^2}, \tag{7}$$

$$\frac{\partial \mathcal{O}}{\partial \gamma} = \sum_{s_{ij} \in S} h(s_{ij}, v_i, w_i) - \sum_{s_{ij} \in S} h(s_{ij}, v_i, w_i) \times P_{(y,s)|\mathcal{G}} - \sum_{s_{ij} \in S} \frac{\gamma^2}{2\sigma^2}. \tag{8}$$
Algorithm 1: The Mutual Gradient Descent (MGD) algorithm

Input: The social graph $G$, number of iterations $n$, and the learning rate $\eta$.

Output: Optimized parameters $\Theta^* = \{\alpha^*, \beta^*, \gamma^*\}$.

while equilibrium states or a threshold number of iterations are not reached do
  repeat
    Choose a random example $(y_i, s_{ij}) \in G$;
    Optimize social action parameters $\alpha$ and $\beta$:
      Compute the approximated gradients $\frac{\partial O'}{\partial \alpha}$ and $\frac{\partial O'}{\partial \beta}$ according to Eq. (3), Eq. (4) and stochastic approximation;
      Update $\alpha$ and $\beta$ with learning rate $\eta$: $\alpha \leftarrow \alpha - \eta \cdot \frac{\partial O'}{\partial \alpha}$, $\beta \leftarrow \beta - \eta \cdot \frac{\partial O'}{\partial \beta}$.
    // Explore social tie influence
    Optimize social tie parameters $\gamma$ and $\beta$:
      Compute the approximated gradients $\frac{\partial O'}{\partial \gamma}$ and $\frac{\partial O'}{\partial \beta}$ according to Eq. (3), Eq. (4) and stochastic approximation;
      Update $\gamma$ and $\beta$ with learning rate $\eta$: $\gamma \leftarrow \gamma - \eta \cdot \frac{\partial O'}{\partial \gamma}$, $\beta \leftarrow \beta - \eta \cdot \frac{\partial O'}{\partial \beta}$.
  end
  until converge;

return $\alpha^*$, $\beta^*$, and $\gamma^*$

It is worth noting that the MGD algorithm computes approximations of the gradients, due to the intractability of the normalizing constant $Z$ in the log-likelihood of our MLRG model. Our proposed MGD algorithm is a generalized extension and it distinguishes from the standard SGD algorithm in two aspects: (1) MGD optimizes three types of parameters simultaneously, thus MGD is much more general than SGD, and it is more scalable and applicable to real-world problems. (2) MGD performs mutual and collaborative optimization to enable mutual influence between social actions and social ties, whereas SGD does not take such influence into account.

4.2 Inference

The objective of inference is to find the most likely types of actions $y^*$ and corresponding social tie labels $s^*$, that is, to find $(y^*, s^*) = \arg \max_{(y, s)} P_{y, s|G}$. The inference procedure is straightforward. Based on the learned parameters $\Theta^* = \{\alpha^*, \beta^*, \gamma^*\}$, we firstly predict the label of each social action $y_i$ by finding a labeling assignment that maximizes $P_{y_i|G}$ as $y^*_i = \arg \max_{y_i \in Y} P_{y_i|G}$. We then infer the social tie label $s_{ij}$ such that $s^*_ij = \arg \max_{s_{ij} \in S} P_{s_{ij}|(y_i, y_j)}$.

5 Experiments

5.1 Foursquare Data

We crawled one dataset from the popular location-based mobile social networking site Foursquare for experimental evaluation. Foursquare allows a user to check in at a physical location via his cellphone, and then let his online friends know where he is by publishing such check-in action online. To alleviate the data sparsity problem for better evaluation, we selected check-in venues which have been visited by at least two distinct users, and users who have checked in at least 10 distinct venues. The resulting dataset contains 11,326 distinct users, 182,968 venues, 1,385,223 check-in behaviors and 47,164 social connections from January 2011 to July 2011. The average check-ins per user is 122.3. All user and venue information has been anonymized. Each check-in has a unique id as well as the user id and the venue id, and each social connection consists of two users represented by two unique ids.

5.2 Evaluation Methodology

We exploited a wide range of important features to define the factors $\phi(\cdot)$, and $\phi'(\cdot)$, including temporal and social features such as the number of check-ins and number of new check-ins in a user’s history, number of friends of a user, the check-in information from a user’s friends, etc. For the coupled latent

---

1https://foursquare.com/
factor $\phi_h(\cdot)$, we incorporated social tie evidences and hypotheses as features to capture social actions, and we also incorporated social action evidences and hypotheses as features to leverage social actions.

<table>
<thead>
<tr>
<th>Models</th>
<th>Precision</th>
<th>Recall</th>
<th>F-measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>73.75</td>
<td>64.54</td>
<td>68.84</td>
</tr>
<tr>
<td>ERGM</td>
<td>80.69</td>
<td>79.70</td>
<td>80.19</td>
</tr>
<tr>
<td>DCRF</td>
<td>89.45</td>
<td>82.32</td>
<td>85.74</td>
</tr>
<tr>
<td>MLRG</td>
<td>89.03</td>
<td>87.89</td>
<td>88.46</td>
</tr>
</tbody>
</table>

Table 1: Comparative performance of different models for social action prediction. The best results are printed in boldface.

<table>
<thead>
<tr>
<th>Models</th>
<th>Precision</th>
<th>Recall</th>
<th>F-measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>70.75</td>
<td>61.57</td>
<td>65.84</td>
</tr>
<tr>
<td>ERGM</td>
<td>78.85</td>
<td>77.39</td>
<td>78.11</td>
</tr>
<tr>
<td>DCRF</td>
<td>82.45</td>
<td>76.56</td>
<td>79.40</td>
</tr>
<tr>
<td>MLRG</td>
<td>84.33</td>
<td>83.89</td>
<td>84.11</td>
</tr>
</tbody>
</table>

Table 2: Comparative performance of different models for social tie inference. The best results are printed in boldface.

For quantitative performance evaluation, we used the standard measures of Precision (P), Recall (R), and F-measure (the harmonic mean of P and R: $\frac{2PR}{P+R}$) for both social action prediction and social tie inference. We performed four-fold cross-validation on this dataset, and took the average performance. We compared our approach with the following alternative methods for predicting social actions and inferring social ties:

– SVM: This model views social action prediction and social tie inference as two separate classification problems, and solves them independently.

– ERGM: This is the traditional exponential-family random graph model without the latent factor $\phi_h(\cdot)$ incorporated for social action prediction and social tie inference.

– DCRF: This model is a dynamical and factorial CRF (Sutton et al., 2007) used to jointly solve the two tasks. This model was originally proposed for labeling and segmenting sequence data.

All these models exploited standard parameter learning and inference algorithms in our experiments. To avoid over-fitting, penalization techniques on likelihood were also performed. All experiments were performed on the Linux workstation, with 24 2.5GHz Intel Xeon E5-2640 CPUs and 16 GB of memory.

5.3 Performance

Table I shows the performance on social action prediction and Table II shows the performance on social tie inference of different models, respectively. Our method consistently outperforms other comparative methods on F-measure. The improvement is statistically and significantly better according to McNemar’s paired tests. These results not only imply that there exists high correlation and mutual influence between social actions and social ties, but also demonstrate the feasibility and effectiveness of our model for exploring them.

The SVM model solves social action prediction and social tie inference independently without considering mutual influence and benefits between them, thus leading to the worst performance. The ERGM outperforms SVM by capturing social network structures. However, the performance of this model is still limited and there is a large room for improving. The DCRF model easily outperforms both SVM and ERGM by modeling social actions and social ties jointly in a single framework. However, compared to our MLRG model, there are still some shortcomings of DCRF. DCRF was proposed to label and segment sequence data, such as POS tagging and NP chunking (Sutton et al., 2007). The graphical structure of DCRF is not well suited for social networks to capture mutual influence. The merits of our proposed MLRG model over other models principally come from (1) appropriate graphical structure for social network modeling, especially the coupled latent factor to exploit mutual influence simultaneously, and (2) the mutual and collaborative learning algorithm MGD to reinforce the optimization of both social actions and social ties.

5.4 Effect of Mutual Influence

We also examined the nature and effectiveness of the associated latent factors on the mutual influence, and Figure 2 demonstrates their feasibility in our modeling. Note that if we do not incorporate the latent factors, our MLRG model becomes the traditional ERGM baseline approach. It shows that the latent factors consistently enhance precision, recall, and F-measure for both social action prediction and social
tie inference tasks. For example, the latent factors significantly improve the F-measure by 8.27% (from 80.19 to 88.46) for social action prediction, and improve the F-measure by 6.0% (from 78.11 to 84.11) for social tie discovery, respectively. These results also illustrate that social actions and social ties influence each other to a large extent.

5.5 Efficiency

Table 3 summarizes the efficiency of several alternative optimization algorithms for learning our model’s parameters. We compared the learning time (hr.) and inference time (sec.) of the MGD algorithm to loopy belief propagation (LBP), Markov chain Monte Carlo (MCMC) Gibbs sampling (Geman and Geman, 1984), and variational mean-field (VMF) approximation algorithms (Wainwright and Jordan, 2008). Both Sutton et al. (2007) and Tang et al. (2011) used LBP for parameter estimation. LBP is inherently unstable and may cause convergence problems. When the graph has large treewidth as in our case, the LBP algorithm is inefficient, and is slow to converge. In Gibbs sampling, the candidate sample is always accepted with the probability of 1, lacking the capability of measuring quality of samples and eliminating low grade samples. The VMF approach aims to minimize the Kullback-Leibler (KL) divergence between an approximated distribution \( Q \) and the target distribution \( P \) by finding the best distribution \( Q \) from some family of distributions for which an inference is feasible. The MGD algorithm we proposed is very efficient. It is particularly notable that our MGD algorithm takes much less time than other three algorithms for learning. In particular, our proposed algorithm is over orders of magnitude faster than the LBP for running.

6 Conclusions and Future Work

Finally, we answer the questions in Section 1 to draw the conclusions of this paper:

Is there any dynamics or mutual influence between social actions and social ties? Doubtlessly, social actions and social ties are highly correlated and mutually reinforced. We propose a single unified framework, mutual latent random graph (MLRG), to exploit homophily for simultaneous social action prediction and social tie discovery. The MLRG model incorporates coupled latent factors to capture dynamics and mutual influence between social actions and social ties. Moreover, we propose the mutual gradient descent (MGD) algorithm to perform mutual and collaborative optimization to reinforce both social actions and social ties. By coupling actions with ties jointly in a single coherent framework, MLRG achieves significantly better performance on both social action prediction and social tie inference, compared to several state-of-the-art existing models.

To what extent do they influence each other? Experimental results on real-world Foursquare data demonstrate that social actions and social ties influence each other to a considerable degree. For example, the latent factors in our model significantly improve the F-measure by 8.27% (from 80.19 to 88.46) for social action prediction, and improve the F-measure by 6.0% (from 78.11 to 84.11) for social tie discovery, respectively.

Two directions of future work appear attractive: Inferring fine-grained and multiple relationships between users (such as friendship, family, colleague, and advisor-adviser, etc.) on complex social networks and extending our established optimization algorithms for parallel and distributed learning based on the Hadoop MapReduce framework to handle large scale social networks involving billions of users.

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Learning Time (hr.)</th>
<th>Inference Time (sec.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LBP</td>
<td>8.67</td>
<td>8</td>
</tr>
<tr>
<td>MCMC</td>
<td>3.45</td>
<td>124</td>
</tr>
<tr>
<td>VMF</td>
<td>2.39</td>
<td>7</td>
</tr>
<tr>
<td>MGD</td>
<td>0.45</td>
<td>6</td>
</tr>
</tbody>
</table>

Table 3: Efficiency comparison of different optimization algorithms on learning time (hr.) and inference time (sec.).
References


