Social Role-Aware Emotion Contagion in Image Social Networks

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Abstract

Psychological theories suggest that emotion represents the state of mind and instinctive responses of one's cognitive system (Cannon 1927). Emotions are a complex state of feeling that results in physical and psychological changes that influence our behavior. In this paper, we study an interesting problem of emotion contagion in social networks. In particular, by employing an image social network (Flickr) as the basis of our study, we try to unveil how users' emotional statuses **influence** each other and how users' **positions** in the social network affect their influential strength on emotion. We develop a probabilistic framework to formalize the problem into a role-aware contagion model. The model is able to predict users' emotional statuses based on their historical emotional statuses and social structures. Experiments on a large Flickr dataset show that the proposed model significantly outperforms (+31% in terms of F1-score) several alternative methods in predicting users' emotional status. We also discover several intriguing phenomena. For example, the probability that a user feels happy is roughly linear to the number of friends who are also happy; but taking a closer look, the happiness probability is superlinear to the number of happy friends who act as *opinion leaders* (Page et al. 1999) in the network and sublinear in the number of happy friends who span *structural holes* (Burt 2001). This offers a new opportunity to understand the underlying mechanism of emotional contagion in online social networks.

1 Introduction

With the rapid development of online social networks such as Facebook[1], Twitter[2], and Flickr[3], it becomes easier for people to connect with each other and share life experiences by posting messages online. In the meantime, statistics show that 10% of the tweets on Twitter contain an emotion icon. Thus an interesting question here is: will one's emotional status influence others around them? For instance, when you feel happy, will the happiness spread through your social network?

Emotion contagion is a process in which a person or group influences the emotions or behavior of another person or group, which was previously studied by psychologists through interviews with small groups of participants. For example, Fowler and Christakis (Fowler, Christakis, and others 2008) presented the theory of three degree of influence. They find that when one feels happy, her/his friends will have a higher probability than chance to become happy. Existing research on Facebook also has demonstrated that emotion contagion does occur via text-based computer-mediated communication (Guillory et al. 2011). Comparing with text, image is a more subjective and ambiguous media for people to communicate. Besides text-based communications, will emotion contagion occur in image social networks? This is the first question we aim to justify in this work.

Moreover, researchers find that users occupying different positions in the social network play very different roles when spreading information (Yang et al. 2015). For example, 1% of users acting as *opinion leaders* (Page et al. 1999), who are taking central positions within communities, post 50% of URLs on Twitter (Wu et al. 2011). In the meantime, 1% of users serving the role of *structural hole spanners*, who are bridges between otherwise disconnected communities in a network (Burt 2009), control 25% of information diffusion (Lou and Tang 2013). Comparing with propagating a piece of information, will these users have different patterns when propagating emotional status? This is the second question we aim to answer.

Recently, the problem of emotional status inference has attracted considerable research effort. For example, (Yang et al. 2014) studied the problem of inferring emotions from images by jointly modeling images posted by users and comments added by their friends. The problem was also studied in mobile social networks, using users' attributes like posted blogs, locations and calling logs to infer their emotional status (Tang et al. 2012). In the meantime, a public report on Facebook data suggests that images drive event engagement 100 times faster (e.g., clicking "like" or adding comment) than text (Wang et al. 2015). However, these methods treat each individual independently and ignore the correlations/influence among them. How to better infer the emotional status of users in social networks by considering emotion contagion, or more precisely, the social-role aware emotion contagion, is our final goal in this work.

In this paper, to answer the three questions above, we conduct several analysis and experiments by employing a

[1]http://facebook.com
[2]http://twitter.com
[3]http://flickr.com

widely used image social network (Flickr) data as the basis.

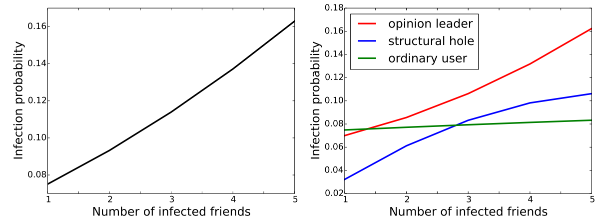
First of all, emotion contagion does exist in image social networks. We take contagion of happiness as an example to briefly introduce our results. As Figure 1(a) shows, when the number of a user's friends being happy increases, the probability that she will also be happy grows, which implies that the emotional status of a user will be influenced by her friends.

Secondly, social roles and emotion contagion are not independent of each other. As shown in Figure 1(b), the probability that a user becomes happy is superlinear to the number of her happy friends who act as opinion leaders, and is sublinear in the number of happy friends who span structural holes. Furthermore, we also find that people tend to be influenced by opinion leaders and structural hole spanners to feel positive emotions (e.g., happiness), and tend to be influence by ordinary users to feel negative emotions (e.g., sadness). This is different from information diffusion, in which case opinion leaders and structural hole spanners tend to have stronger influence than ordinary users (Yang et al. 2015). See more details in Section 3.

Based on the two findings, we propose the problem of social role-aware emotion contagion and seek to infer the dynamics of users' emotional status in a given online social network. The problem is non-trivial and holds several challenges. The first challenge is how to uncover the social roles that users play in emotional contagion. Then, within emotional contagion, users with different social roles may function in different ways. Distinguishing the patterns corresponding to each social role is the second challenge. The last and greatest challenge is computational complexity. Emotional status may be propagated through any pair of users, which causes the hypothesis space of diffusion paths to grow exponentially with the number of users. At the same time, traditional influence models aim to learn the strength between each pair of users in a given network, which is impractical, as real networks include large numbers of users. Given these circumstances, designing an effective model to trace emotional contagion is a challenging issue of this work.

To address the above challenges, we propose a probabilistic graphical model, *social role-aware contagion model*, and summarize our technical contributions as follows:

- We design three kinds of factor functions in the proposed model, based on the discoveries in our empirical analysis. The functions capture underlying mechanism of how social roles of users influence emotion contagion and make our model to describe the contagion process more precisely.
- We reduce the model complexity by projecting parameters into a lower-dimensional space, supported by our discovery that users with the same social role share similar parameters in emotion contagion. Thus, different from traditional contagion/influence models, the learning process of our model becomes practical.
- We conduct extensive experiments to validate the proposed model over several baselines. Experimental results show that the proposed model achieves a +31.7% improvement, on average, over other approaches.



(a) Role unaware (b) Role aware

Figure 1: Emotion contagion analysis on Flickr.In the figure, x-axis indicates the number of user v's friends (with a particular social role) being happy, while y-axis represents the probability that v is happy.

2 Problem Definition

We are given a social network that represents the relationships between users, in which users can post images. We formally define the set of images as M. For each image $m \in M$, we have the user v_m who has posted m, the timestamp t_m when m is posted, and a K dimensional vector $x_m =< x_{m1}, \cdots, m_{mK} >$ ($\forall_k, x_{mk} \in \mathbb{R}$), where x_{mk} indicates the k-th visual feature (e.g., e.g., saturation, cool color ratio, etc.) of m.

More precisely, we incorporate images and social network information in an image social network.

Definition 1 *An **image social network** is a directed graph $G =< V, M, E, R >$. There are two vertex sets: V, a set of users, and M, a set of images. Edges in E represent user-user relations $\{(u, v)|u \in V, v \in V\}$, indicating that u follows v, and user-image relations $\{(v, m)|v \in V, m \in M\}$, indicating that v posts m. R denotes social roles of users, where r_v is the social role of user v.*

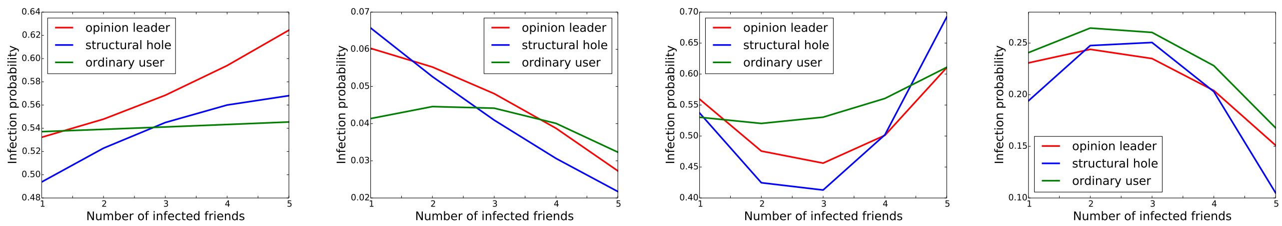
In this work, we aim to study emotion contagion in a given image social network G. We use a $T \times V$ matrix $\mathbf{Y}$ to denote users' emotional status, where y_{vt} indicates v's emotion at time t ($\forall_t, t \leq T$). For users' emotional status, in this work, we mainly consider Ekman's six emotions (Ekman 1992): {happiness, surprise, anger, disgust, fear, sadness}. We define the prediction task addressed in this paper as below:

Definition 2 ***Emotion contagion inference.*** *Given an image social network G, a specific time t, and emotional status of users within time $[1, t-1]$, our goal is to learn a function*

$$f : G = (V, M, E, R), t, Y_{\cdot 1 \cdots t-1} \rightarrow Y_{\cdot t} \quad (1)$$

3 Exploratory Analysis

Goal. In this section, we present several exploratory analyses to uncover the underlying mechanism of the influence between social roles and emotion contagion. More specifically, how users with different social roles influence their friends with different emotional contagions. We conduct all



(a) happiness→happiness (b) anger→happiness (c) happiness→fear (d) fear→fear

Figure 2: The influence between different social roles and emotion contagion.

experiments in this paper based on Flickr[4]. See more details of our dataset in Section 5.

Setting. We first need to identify social roles of users. Inspired by the work in (Yang et al. 2015), we categorize users into three roles, namely *opinion leaders*, *structural hole spanners*, and *ordinary users*, based on their network properties. Specifically, we consider 20% of users with the highest PageRank scores (Page et al. 1999) to be opinion leaders, 20% of users with the lowest Burt's network constraint scores (Burt 2001) to be structural hole spanners, and the remaining as ordinary users. Notice that the percentage of users defined as each social role will influence the experimental results. We examine this influence in detail in Section 5. We then define infection probability as the probability that a user has a particular emotional status. We are interested in how users' infection probabilities are influenced by their friends with different social roles. Specifically, Figure 2 depicts the probability of a user being happy (a-b), or in a state of fear (c-d), when she is influenced by different numbers of her friends, with different social roles, who are happy (a,c), angry (b), or fear (d).

Results. Generally, we find the following results from Figure 2: 1) from (a) and (b), we see that positive emotion tends to delight friends, making them be more happy and less angry; 2) from (c) and (d), we see that when there are 1-2 friends of a user being negative emotion (e.g., fear), that user will tend to be less happy and more fear; 3) however, when the number of infected friends continue increasing (more than 3), the user will be more happy and less fear. This phenomena suggests the existence of "emotional comfort": when a user is surrounded by a few friends with negative emotions, the user and her friends will comfort each other and get better mood.

From the figure, we further compare how different social roles behave in emotion contagion. We first see that opinion leaders are most influential when they are happy, while ordinary users have more influence when they have negative emotional status (e.g., fear). Intuitively, opinion leaders and structural hole spanners are not necessarily as close to their friends as ordinary users. Secondly, we observe that, as the number of infected friends grows, infection probabilities of opinion leaders and structural hole spanners change faster than ordinary users.

As a conclusion, we find that users with different social roles influence their friends with different influential strengths. Moreover, different with information diffusion, in which case opinion leaders and structural hole spanners tend to have stronger influence than ordinary users (Yang et al. 2015), in emotion contagion, opinion leaders and structural hole spanners may be less influential than ordinary users. Specifically, users with these two social roles are more influential on positive emotion contagion, while ordinary users have more influence on negative emotion contagion.

4 Proposed Model

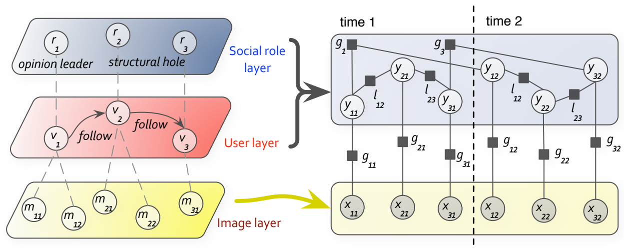
Intuition. We propose a graphical model, *social role-aware contagion model*, to describe the emotion contagion in a given social network. Intuitively, given a time t, the emotional status of a user v, y_{vt}, will be influenced by the emotional status of her friends at $t-1$. According to our discoveries in Section 3, the influence strength will be determined by the social roles of v's friends. Besides, y_{vt} also depends on v's own emotional status at time $t-1$. At last, the images posted by user v at time t is able to express her current emotional status.

Thus, the general idea of the proposed model is to 1) learn the influence strength between friends by considering their social roles; (2) learn the dependency between emotions of the same user at adjacent time stamps; (3) learn how images posted by users reflect users' emotions. We then will be able to predict the emotional status of users.

Description. The goal of the proposed model is to maximize the conditional probability of users' emotional status over time, given an image social network, i.e., $P(\mathbf{Y}|G)$. More precisely, we regard a particular emotion contagion log (v, t, y_{vt}) as an instance, which represents that user v has emotional status y_{vt} at time t. We then learn the model to find a configuration of parameters, which maximizes the joint conditional probability of all instances. When applying the learned model to predict the complete emotion contagion, it tries to find a setting of emotion contagion logs $Y_{\cdot t+1}$ at time $t+1$ to maximize the conditional probability $P_\theta(Y_{\cdot t+1}|G)$ based on the learned parameters.

The inference of conditional probability $P(\mathbf{Y}|G)$ is often intractable. Factor graph factorizes the "global" probability as a product of "local" factor functions, each of which depends on a subset of variables in the graph (Kschischang,

[4]http://flickr.com, the largest photo sharing website



(a) An example of the problem
(b) Social Role-Aware Contagion Model

Figure 3: Graphical representation of the proposed model.

Frey, and Loeliger 2001). In the proposed model, inspired by the observation results, we try to capture three kinds of information, *image features*, *self-contagion*, and *pairwise-contagion*. Specifically, we represent them by using three factor functions, respectively.

- Pairwise-contagion factor: $l(y_{ut-1}, y_{vt})$ represents how user v's emotional status at time t is influenced by her friend u 's emotional status at time $t-1$, where $e_{vu} \in E$.
- Self-contagion factor: $h(y_{vt-\Delta t}, y_{vt})$ represents the correlation between user v's emotional status at time t and time $t - \Delta t$. It seeks to model how one's emotional status changes over time.
- Attribute factor: $g(x_{vt}, y_{vt})$ represents the correlation between user v's emotional status at time t (i.e., y_{vt}) and the visual features of the image she posts at the same time (i.e., x_{vt}).

We introduce the graphical structure of our model as illustrated in Figure 3. The observed data contains three layers: social roles of users, users and their relationships, also the images posted by users. We extract the visual features from images and represent the features as $\mathbf{x}$. We model v_1's emotional status at time 2 as y_{12}, which depends on her emotional status at preceding time (y_{11}), and the emotional status of her friend v_2 at time 1 (y_{21}).

We then formally define each factor. We begin with the attribute factor $g(x_{vt}, y_{vt})$. The intuition behind this factor is, image is able to express one's emotions. For example, according to existing work (Yang et al. 2014), an image with higher saturation and bright contrast was probably posted by a happy user. Specifically, given an image's feature vector x_{vt}, we define $g(x_{vt}, y_{vt})$ as

$$g(x_{vt}, y_{vt}) = \frac{1}{Z_1} \exp\{\alpha_{y_{vt}} \cdot x_{vt}\} \quad (2)$$

where α is a vector of real valued parameters; and Z_1 is a normalization term to ensure that the distribution is normalized so that the sum of the probabilities equals to 1.

We next define self-contagion factor function by capture how one's emotional status changes over time as

$$h(y_{vt-\Delta t}, y_{vt}) = \frac{1}{Z_2} \exp\{\beta_{\Delta t} \cdot I(y_{vt-\Delta t}, y_{vt})\} \quad (3)$$

where $\beta_{\Delta t}$ is a decay weight with respective to time interval Δt; $I(\cdot)$ is defined as a vector of indicator functions; and Z_2 is a normalization term. In practice, we consider Δt is ranged within a predefined interval, such as $[1, 5]$, to reduce the computational complexity of the proposed model.

As the analysis conducted in Section 3 suggests, a user's emotional status will be influence by her friends. Also, social roles affects the influence strength. To capture this information, we define the pairwise-contagion factor as

$$l(y_{ut-1}, y_{vt}) = \frac{1}{Z_3} \exp\{\gamma_{r_u r_v} \cdot I(y_{ut-1}, y_{vt})\} \quad (4)$$

where γ is a matrix indicating the influence strength between different social roles, $\gamma_{rr'}$ denotes the influence strength between a user with social role r and another user with social role r', Z_3 is a normalization term.

By integrating all the factor functions together, and according to the Hammersley-Clifford theorem (Hammersley and Clifford 1971) we obtain the following log-likehood objective function.

$$\begin{aligned} \mathcal{O}(\theta) &= \log P_\theta(Y|G) \\ &= \sum_t \sum_v \alpha_{y_{vt}} x_{vt} + \sum_t \sum_v \sum_{\Delta t} \beta_{\Delta t} I(y_{vt-\Delta t}, y_{vt}) \\ &+ \sum_t \sum_v \sum_{u, e_{vu} \in E} \gamma_{r_u r_v} I(y_{ut-1}, y_{vt}) - \log Z \end{aligned} \quad (5)$$

where $\theta = \{\alpha, \beta, \gamma\}$ is a parameter configuration of the proposed model; and Z is a normalization term.

Traditional influence models, e.g., (Goyal, Bonchi, and Lakshmanan 2010) (Kimura et al. 2011) (Kempe, Kleinberg, and Tardos 2003), which aim to learn the strength between each pair of users in a given network, have $O(E)$ parameters to learn, where E is the number of edges. We reduce model complexity to $O(|R|)$ ($|R|$ is the total number of social roles), by letting users with same social roles share same parameters, and make it practical to learn the model.

Feature definition. We utilize the visual features proposed by Wang et al. (Wang et al. 2013), which are mainly aesthetics-based and include saturation, saturation contrast, bright contrast, cool color ratio, figure-ground color difference, figure-ground area difference, foreground texture complexity, and background texture complexity.

Model learning. Learning the proposed model is to find a configuration for the free parameters $\theta = \{\alpha, \beta, \gamma\}$ that maximizes the log-likelihood objective function $\mathcal{O}(\theta)$.

We introduce gradient descent method to solve the function. The gradient for each parameter μ is calculated as:

$$\begin{aligned} \nabla &= \frac{\partial \log P(Y|G, \theta)}{\partial \theta} \\ &= \mathbb{E}_{P_\theta(Y^U|G,\theta)} \mathbf{Q}(Y^U) - \mathbb{E}_{P_\theta(Y|G,\theta)} \mathbf{Q}(Y) \end{aligned} \quad (6)$$

where Y^U are the unknown labels. One challenge here is to directly calculate the two expectations. The graphical structure of our model may be arbitrary and contain cycles. Thus, we adopt Loopy Belief Propagation (LBP) (Murphy, Weiss, and Jordan 1999) approximate algorithm to compute the marginal probabilities of Y and Y^U. We are then able to obtain the gradient by summing over all the label nodes. An important point here is that the LBP process needs to be proceeded twice during the learning procedure, one for estimating $P(Y|G,\theta)$ and again for $p(Y^U|G,\theta)$. We update each parameter with a learning rate λ with the gradient.

5 Experimental Results

5.1 Experimental Setup

Dataset. We conduct all experiments in this paper based on Flickr. Specifically, we randomly download 2,060,353 images and 1,255,478 users who post these images along with their profiles from Flickr. How to measure emotions is a key question in affective computing. Facing the vast scale of social images, manually labeling is powerless. Instead, we use tags and comments for automatic image labeling, which is the common method in previous work (Xie 2013) (Hwang 2013). We use WordNet[5] and HowNet[6] dictionaries to obtain averagely more than 200 synonyms for each emotion category, and manually verify them. For each image, we count the occurrences of each emotion synonym category in its tags and comments, and select the most frequent emotional status (if exists) as the ground truth. In this way, we obtain the distribution of users' emotional status on Flickr: 46.2% happiness, 9.7% surprise, 8.0% anger, 5.3% disgust, 17.3% fear, and 13.5% sadness.

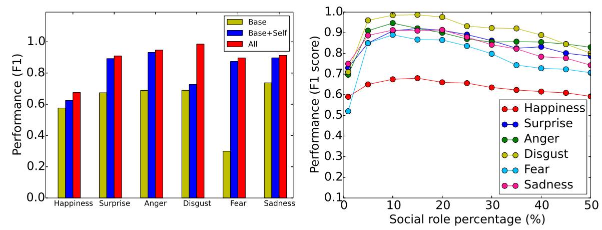
Task and evaluation metrics. Given the input network G and the emotion contagion history $\mathbf{Y}$, we construct a training dataset $\{(\mathbf{x}_{vt}, y_{vt})\}_{v\in V, t=1\cdots T}$, where $\mathbf{x}_{vt}$ is the feature vector associated with user v and time t, and y_{vt} indicates the user v's emotional status at time t. The task in our experiment is to predict users' emotional status in future (time $t+1$). For evaluation, we consider the following performance metrics: Precision, Recall, and F1-score.

Comparison methods.

SVM: it uses all features associated with each user to train a classification model, and then applies it to predict users' emotional status in test data. For SVM, we use LibSVM [7].

LR: it uses logistic regression to train the classification model with the same features as those in the SVM method. We also compare our approach with the results of Naive Bayes (NB), Bayesian Network (BN), and Gaussian Radial Basis Function Neural Network (RBF). For these methods, we employ Weka[8]. The difference between these methods and our model is that they do not consider the influence between users' emotional status.

CRF: it is a graphical model based on Conditional Random Field (CRF). In this method, besides users' features $\mathbf{x}$, we further consider the correlations between users' emotional status. The difference between this method and our model is that CRF ignores the social role information.



(a) Factor analysis. (b) Social role analysis.

Figure 4: Factor and social analysis.

Role-aware: it is our proposed role-aware contagion model. In our experiments, we empirically set the learning rate λ as 0.1 and set the upper bound of Δt as 3 unit timestamps ($1 \leq \Delta t \leq 3$).

5.2 Quantitative Results

Prediction performance. Table 1 lists the emotional status prediction performance of the different methods on the Flickr data set. Our method consistently achieves better performance than the comparison methods. In terms of F1-score, the proposed model achieves a 44.3% improvement, on average, compared with the methods that do not consider correlation features (i.e., SVM, LR, BN, and RBF). CRF also considers some correlation features (the influence between users and timestamps), and thus improves its prediction performance. However it cannot incorporate the social role information, and thus underperforms our method by 19.1% in terms of F1-score. We produced sign tests for each result, which confirms that all the improvements of our proposed models over the five methods are statistically significant ($p \ll 0.01$).

Factor analysis. In the proposed model, we define three types of factors: pairwise-contagion factor, self-contagion factor, and attribute factor. Here we show how these factors contribute in prediction task. Specifically, we first use attribute factor along to train a model (referred to as Base). We then incrementally add the self-contagion factor (referred to as Base+Self) and pairwise-contagion factor (referred to as All) and evaluate their improvements in prediction performance over that using only basic features. Figure 4(a) shows the results. We see that different factors contribute differently in different emotions. For example, the self-contagion factor is very useful when predicting "fear", but less useful when predicting "disgust". Intuitively, "disgust" is an emotion which lasts for a short time, and has less time dependency than "fear". On the other hand, the pairwise-contagion factors improve the prediction performance on all the emotions.

Effects of social roles. We study how different percentage of users playing social roles affect emotion prediction performance. Specifically, before modeling, we define $\rho\%$ of users as opinion leaders and structural hole spanners. We

[5] http://wordnet.princeton.edu/

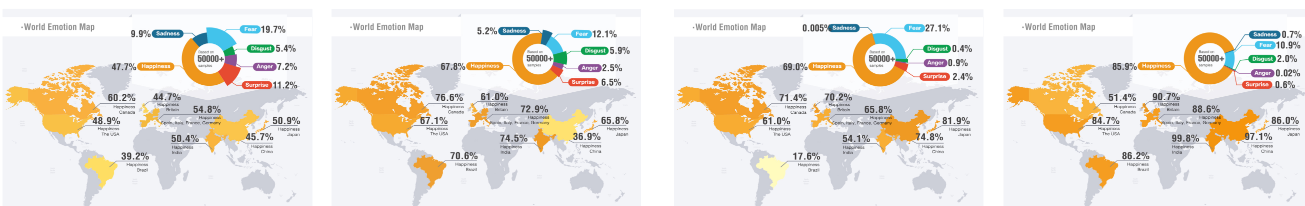
[6] http://www.keenage.com/

[7] http://www.csie.ntu.edu.tw/~cjlin/libsvm/

[8] http://www.cs.waikato.ac.nz/ml/weka/

Table 1: Performance of emotion inference.

Emotion	Method	Precision	Recall	F1-score	Emotion	Method	Precision	Recall	F1-score
	SVM	0.5490	0.4682	0.5054		SVM	0.5721	0.6223	0.5962
	LR	**0.5726**	0.4234	0.4868		LR	0.5902	0.5847	0.5874
	NB	0.5604	0.4679	0.5100		NB	0.5657	0.7244	0.6353
Happiness	BN	0.5605	0.5129	0.5357	Disgust	BN	0.5666	0.6811	0.6186
	RBF	0.5744	0.2676	0.3651		RBF	0.5246	0.4346	0.4754
	CRF	0.5590	0.5938	0.5759		CRF	0.8304	0.5889	0.6891
	Role-aware	0.5285	**0.9327**	**0.6747**		Role-aware	**0.9758**	**0.9947**	**0.9852**
	SVM	0.5103	0.4821	0.4958		SVM	0.5253	0.5521	0.5384
	LR	0.5231	0.4108	0.4602		LR	0.5523	0.4703	0.5080
	NB	0.5124	0.5324	0.5222		NB	0.5350	0.5295	0.5322
Surprise	BN	0.5241	0.4712	0.4963	Fear	BN	0.5446	0.5189	0.5315
	RBF	0.4990	0.1756	0.2597		RBF	0.5227	0.2859	0.3696
	CRF	0.5810	0.8014	0.6736		CRF	0.5074	0.2123	0.2993
	Role-aware	**0.8992**	**0.9181**	**0.9086**		Role-aware	**0.8123**	**0.9996**	**0.8963**
	SVM	0.5186	0.6371	0.5718		SVM	0.5733	0.5740	0.5723
	LR	0.5275	0.4634	0.4934		LR	0.5664	0.4866	0.5234
	NB	0.5201	0.4959	0.5078		NB	0.5632	0.4991	0.5292
Anger	BN	0.5260	0.5207	0.5233	Sadness	BN	0.5730	0.5662	0.5695
	RBF	0.5062	0.2441	0.3294		RBF	0.5344	0.4292	0.4761
	CRF	0.6036	0.8015	0.6886		CRF	0.6382	0.8726	0.7372
	Role-aware	**0.9346**	**0.9593**	**0.9468**		Role-aware	**0.8741**	**0.9550**	**0.9128**



(a) Real distribution. (b) Randomly sampled users. (c) Opinion leaders. (d) Structural hole spanners.

Figure 5: The emotion distributions and happiness degree of users of different social roles around the world.

now examine how different ρ influence the prediction performance. Figure 4(b) shows the results. As we can see, for all emotions, the best performance can be achieved when ρ is within 10 to 20. When ρ is less than 10, the number social roles is too small to benefit the prediction. On the other hand, too many users being regarded as opinion leaders and structural hole spanners, which hurts the performance.

Case study. We finally use a case study to demonstrate how different social roles behave in our prediction task. Figure 5 shows the emotion distributions and the degree of happiness of users from different countries. Specifically, each figure from left to right shows the real emotion distributions and happiness degrees of all users, randomly sampled users, opinion leaders and structural hole spanners, respectively. We see that in most countries, the happiness degrees of structural hole spanners and opinion leaders' are higher than those of the real distribution. This can be explained by the fact that structural hole spanners and opinion leaders are public figures on social networks, who attach much importance to their spreading of positive emotions, while ordinary users tend to share their daily lives.

6 Conclusion

In this paper, we study the interplay between users' social roles and emotion contagion. We find users with social roles of opinion leaders and structural hole spanners tend to be more influential than ordinary users in positive emotion contagion while be less influential in negative emotion contagion. Our discoveries inspire us to propose a role-aware contagion model to predict users' emotional status, which is evaluated on a real social media dataset.

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