Computational Models for Social Influence and Diffusion

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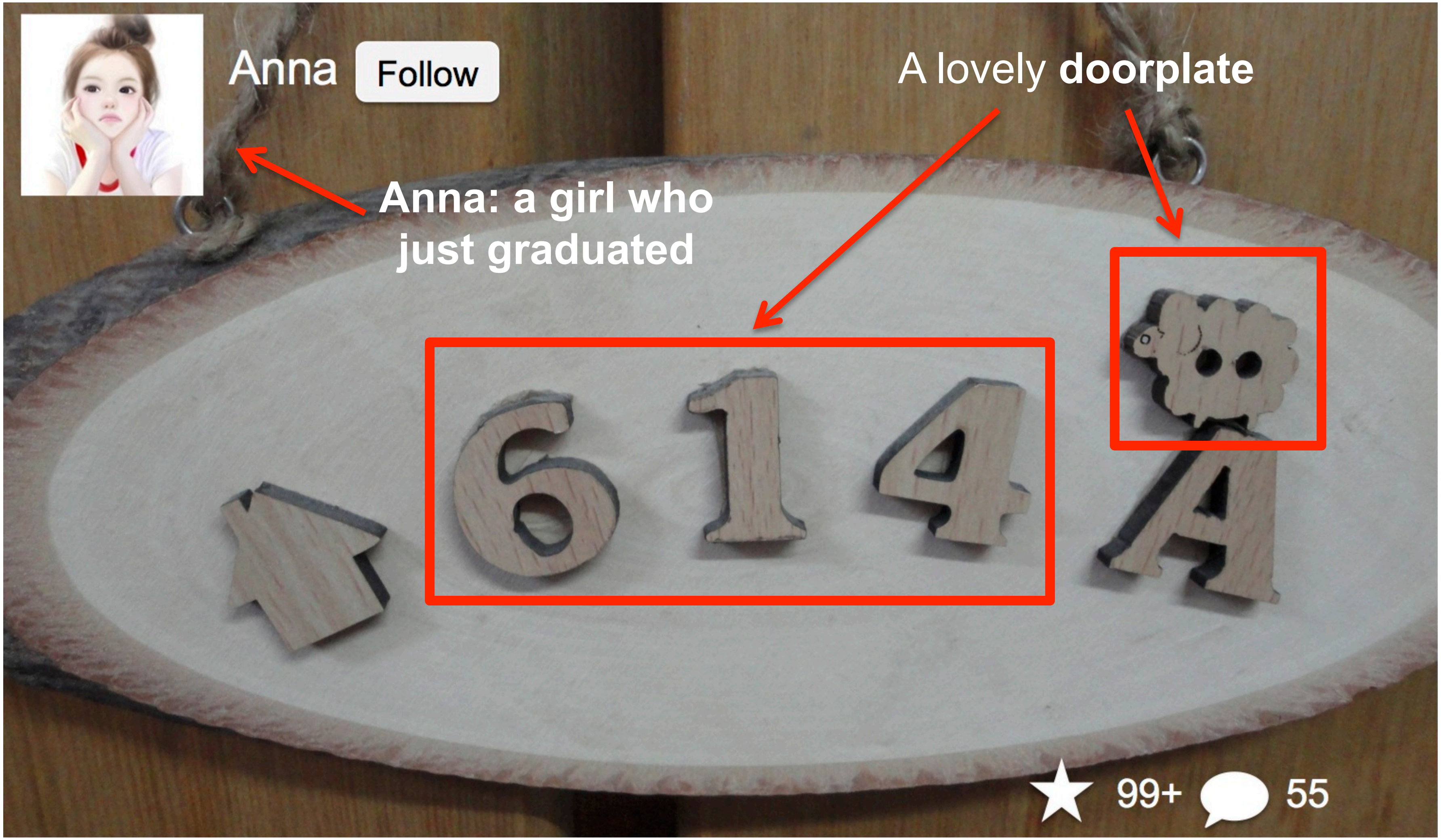
Part II:
User Emotion Influence and Influence based Network Embedding

How Do User Emotions Diffuse in Social Networks?

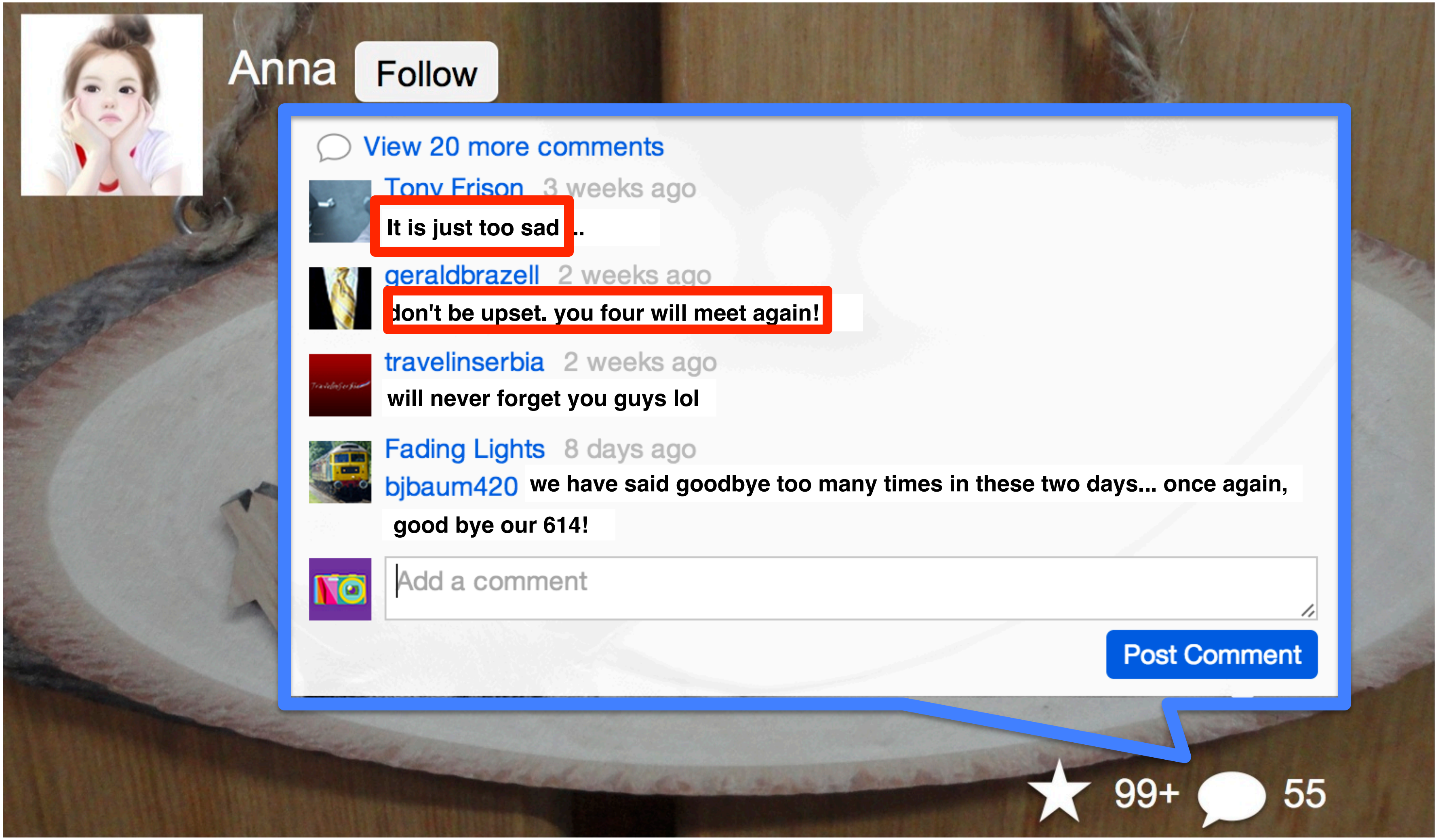
Yang Yang, Jia Jia, Boya Wu, and Jie Tang. **Social Role-Aware Emotion Contagion in Image Social Networks.** AAAI, 2016.

Yang Yang, Jia Jia, Shumei Zhang, Boya Wu, Qicong Chen, Juanzi Li, Chunxiao Xing, and Jie Tang. **How Do Your Friends on Social Media Disclose Your Emotions?** AAAI, 2014.

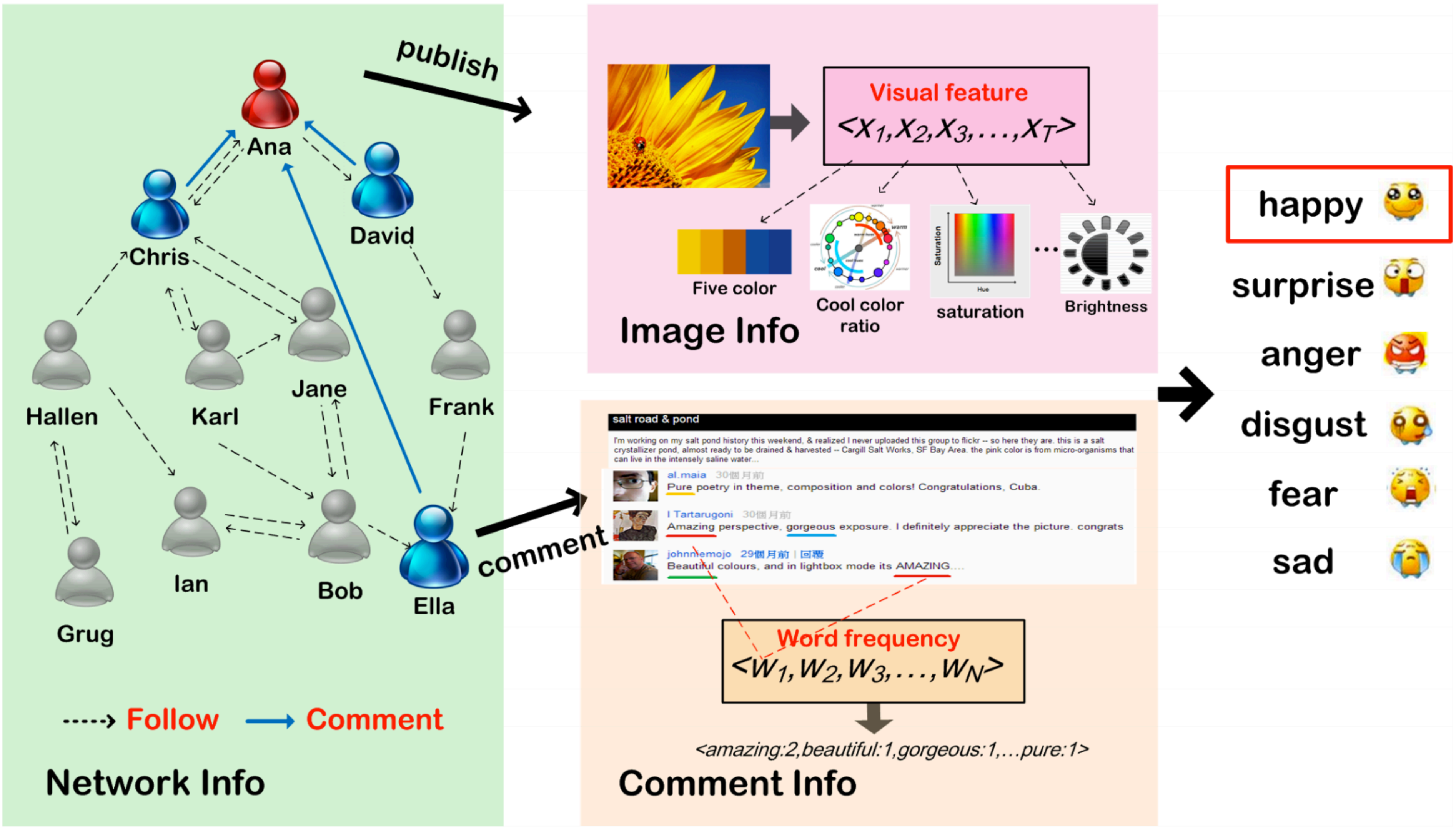
Was Anna Happy When She Published This Photo On Flickr?



To What Extent Your Friends Will Disclose Your Emotions?



Problem



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Predicting Users' Emotional Status

- **Input:** An image social network G=<V, M, D, E, R, L>, where V is a set of users, M is a set of images, D is a set of comments, E represents following relationships between users, each element in R (v, m, t) denotes that user v publishes image m at time t, and an edge in L (v, d, m) indicates that user v leaves a comment d under image m.
- We use a matrix Y to denote users' emotional status, where y_{vt} indicates v's emotion at time t. $y_{vt} \in$ {happiness, surprise, anger, disgust, fear, sadness}
- Task: Given G, Y, a time stamp t, our goal is to learn

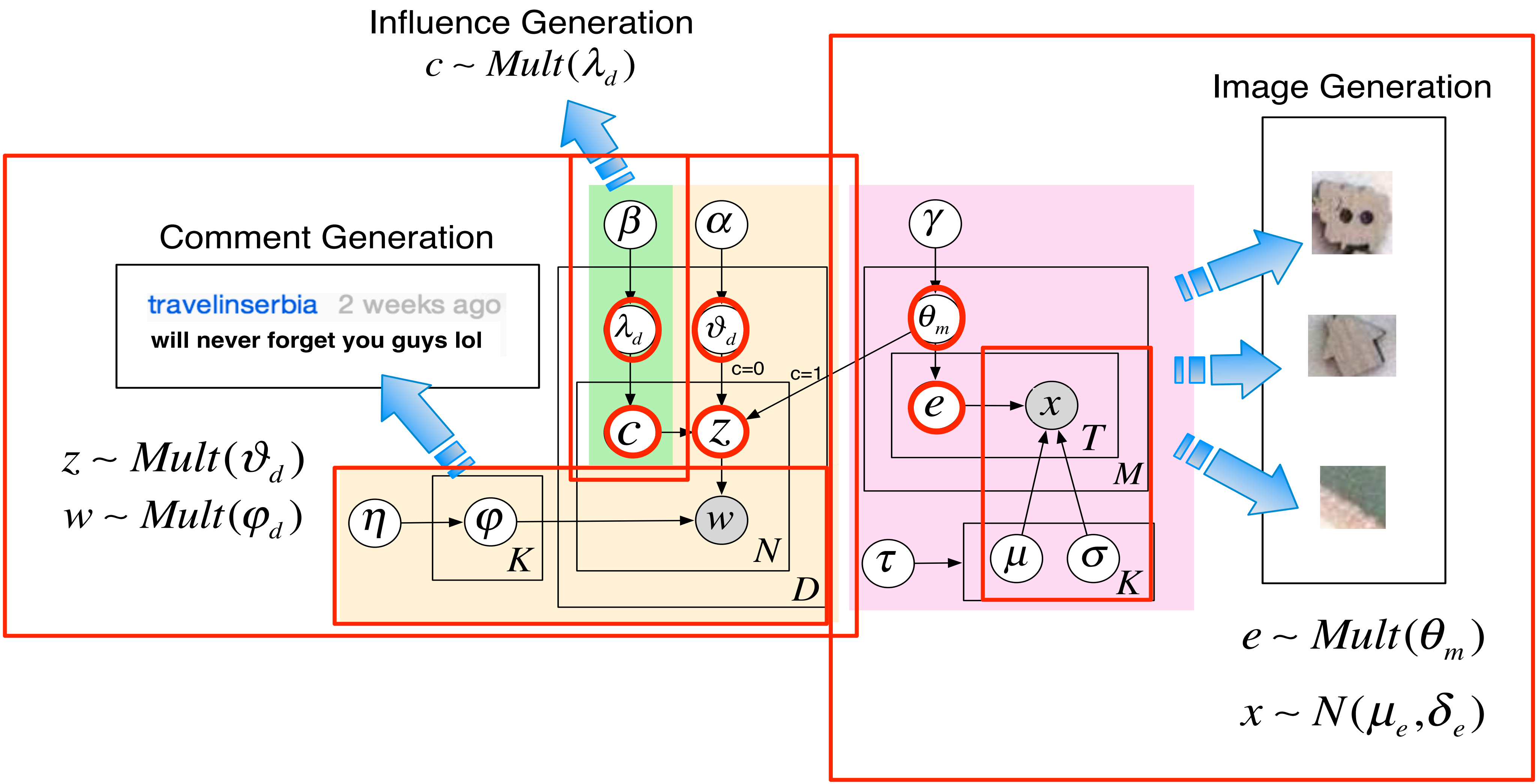
$$f : G = (V, M, E, R), t, Y_{.1 \ldots t-1} \rightarrow Y_{.t}$$

Challenges

- How to model the image information and content information jointly?

- How to learn the association between the implied emotions of different comments?

Emotion Learning Method



Yang Yang, Jia Jia, Shumei Zhang, Boya Wu, Qicong Chen, Juanzi Li, Chunxiao Xing, and Jie Tang. **How Do Your Friends on Social Media Disclose Your Emotions?** AAAI, 2014.

Generative Process

Input: the hyper-parameters α, β_0, b_0, b_1, γ, η, and τ, the image-based social network G

foreach *image* $m \in M$ **do**
    foreach *visual feature* x_{mt} *of* m **do**
        Generate $e_{mt} \sim \mathrm{Mult}(\theta_m)$;
        Generate $x_{mt} \sim N(x_{mt} | \mu_{e_{mt}t}, \delta_{e_{mt}t})$;
    end
    foreach *comment* d*, where* $a_{md} \in A$ **do**
        foreach *word* w_{di} *of* d **do**
            Generate $c_{di} \sim \mathrm{Mult}(\lambda_d)$;
            if c_{di} == *0* **then**
                Generate $z_{di} \sim \mathrm{Mult}(\theta_d)$;
            end
            if c_{di} == *1* **then**
                Generate $z_{di} \sim \mathrm{Mult}(\theta_m)$;
            end
            Generate $w_{di} \sim \mathrm{Mult}(\varphi_{z_{di}})$
        end
    end
end

Algorithm 1: Probabilistic generative process in the proposed model.

Visual feature generation

User influence generation

User comment generation

Learning Algorithm

- We employ Gibbs sampling to estimate unknown parameters.
  - The posterior for sampling the latent variables for each word:

$$P(z_{di}, c_{di} = 0 | \mathbf{z}_{\neg di}, \mathbf{c}_{\neg di}, \mathbf{w}) = \frac{n^{\neg di}_{z_{di}d} + \alpha}{\sum_z (n^{\neg di}_{zd} + \alpha)} \times \frac{n^{\neg di}_{c_{di}d} + \beta_{c_{di}}}{\sum_c (n^{\neg di}_{cd} + \beta_c)} \times \frac{n^{\neg di}_{z_{di}w_{di}} + \eta}{\sum_w (n^{\neg di}_{z_{di}w} + \eta)}$$

#(c_{di} is sampled associated with i-th word in d)

  - The posterior for sampling the latent emotion:

$$P(e_{mt}; \mathbf{e}_{\neg mt}, \mathbf{x}) = \frac{n^{\neg mt}_{me_{mt}} + \gamma}{\sum_e (n^{\neg mt}_{me} + \gamma)} \times \frac{\Gamma(\tau_2 + \frac{n_{e_{mt}t}}{2})}{\Gamma(\tau_2 + \frac{n^{\neg mt}_{e_{mt}t}}{2})} \times$$

$$\frac{\sqrt{\tau_1 + n^{\neg mt}_{e_{mt}t}}[\tau_3 + \frac{1}{2}(n^{\neg mt}_{e_{mt}t} s^{\neg mt}_{e_{mt}t} + \frac{\tau_1 n^{\neg mt}_{e_{mt}t}(\bar{x}^{\neg mt}_{e_{mt}t} - \tau_0)^2}{\tau_1 + n^{\neg mt}_{e_{mt}t}})]^{(\tau_2 + \frac{n^{\neg mt}_{e_{mt}t}}{2})}}{\sqrt{\tau_1 + n_{e_{mt}t}}[\tau_3 + \frac{1}{2}(n_{e_{mi}t} s_{e_{mt}t} + \frac{\tau_1 n_{e_{mt}t}(\bar{x}_{e_{mt}t} - \tau_0)^2}{\tau_1 + n_{e_{mt}t}})]^{(\tau_2 + \frac{n_{e_{mt}t}}{2})}}$$

use Stirling's formula to calculate gamma function

Learning Algorithm (cont.)

- Update for parameters of topic modeling part:

$$\theta_{dz} = \frac{n_{zd} + \alpha}{\sum_{z'} (n_{z'd} + \alpha)} \qquad \theta_{me} = \frac{n_{zm} + \gamma}{\sum_{e'} (n_{e'm} + \gamma)}$$

$$\lambda_{dc} = \frac{n_{cd} + \beta_c}{\sum_{c'} n_{c'd} + \beta_{c'}} \qquad \varphi_{zw} = \frac{n_{zw} + \eta}{\sum_{w'} (n_{zw'} + \eta)}$$

- The update for Gaussian parameters are hard to compute. We approximate Gaussian parameters by their expectations.

$$\mu_{et} \approx E(\mu_{et}) = \frac{\tau_0 \tau_1 + n_{et} \bar{x}_{et}}{\tau_1 + n_{et}}$$

$$\delta_{et} \approx E(\delta_{et}) = \frac{2\tau_2 + n_{et}}{2\tau_3 + n_{et} s_{et} + \frac{\tau_1 n_{et} (\bar{x}_{et} - \tau_0)^2}{\tau_1 + n_{et}}}$$

Flickr Data

- 354,192 images posted by 4,807 users
  - For each image, we also collect its tags and all comments.
  - We get 557,177 comments posted by 6,735 users in total
- Infer emotion of users by considering both image and tag/comments

Emotion Inference

Averagely **+37.4%**
in terms of F1

Table 2: Performance of emotion inference.

Emotion	Method	Precision	Recall	F1-score	Emotion	Method	Precision	Recall	[illegible]
Happiness	SVM	0.242	0.279	0.259	Disgust	SVM	0.192	0.236	0.212
	PFG	0.337	0.312	0.324		PFG	0.309	0.374	0.339
	LDA+SVM	0.333	**0.727**	**0.457**		LDA+SVM	0.223	0.223	0.223
	EL+SVM	**0.367**	0.410	0.388		EL+SVM	**0.331**	**0.432**	**0.374**
Surprise	SVM	0.197	0.037	0.063	Fear	SVM	0.204	0.264	0.230
	PFG	0.349	0.340	0.345		PFG	0.301	**0.408**	0.347
	LDA+SVM	0.218	0.048	0.078		LDA+SVM	0.211	0.225	0.217
	EL+SVM	**0.425**	**0.516**	**0.466**		EL+SVM	**0.371**	0.343	**0.356**
Anger	SVM	0.188	0.105	0.135	Sadness	SVM	0.225	0.365	0.278
	PFG	0.191	0.142	0.163		PFG	0.357	0.286	0.317
	LDA+SVM	0.222	0.109	0.146		LDA+SVM	0.257	0.278	0.267
	EL+SVM	**0.390**	**0.370**	**0.380**		EL+SVM	**0.561**	**0.617**	**0.588**

SVM: regards the visual features of images as inputs and uses a SVM as a classifier.

PFG: considers both color features and social correlations among images.

LDA+SVM: first uses LDA to extract latent topics from comments, then uses visual features, topic distributions, and social ties as features to train a SVM.

To What Extend Your Friends Can Disclose Your Emotions?

-Comments stands for the proposed method ignoring comment information

-Tie ignores social tie information

Fear images have similar visual features with Sadness and Anger.

Homophily suggests that friends with similar interests tend to have similar understanding of disgust

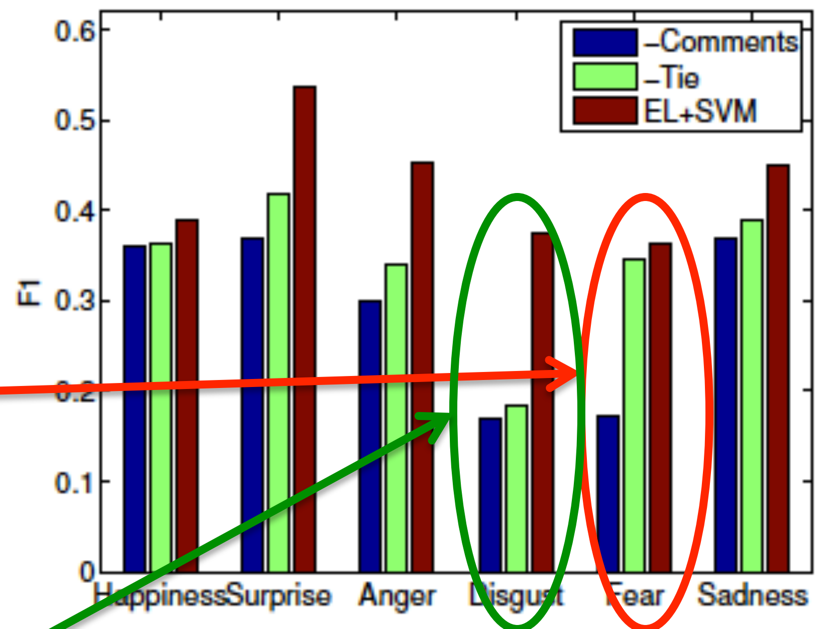
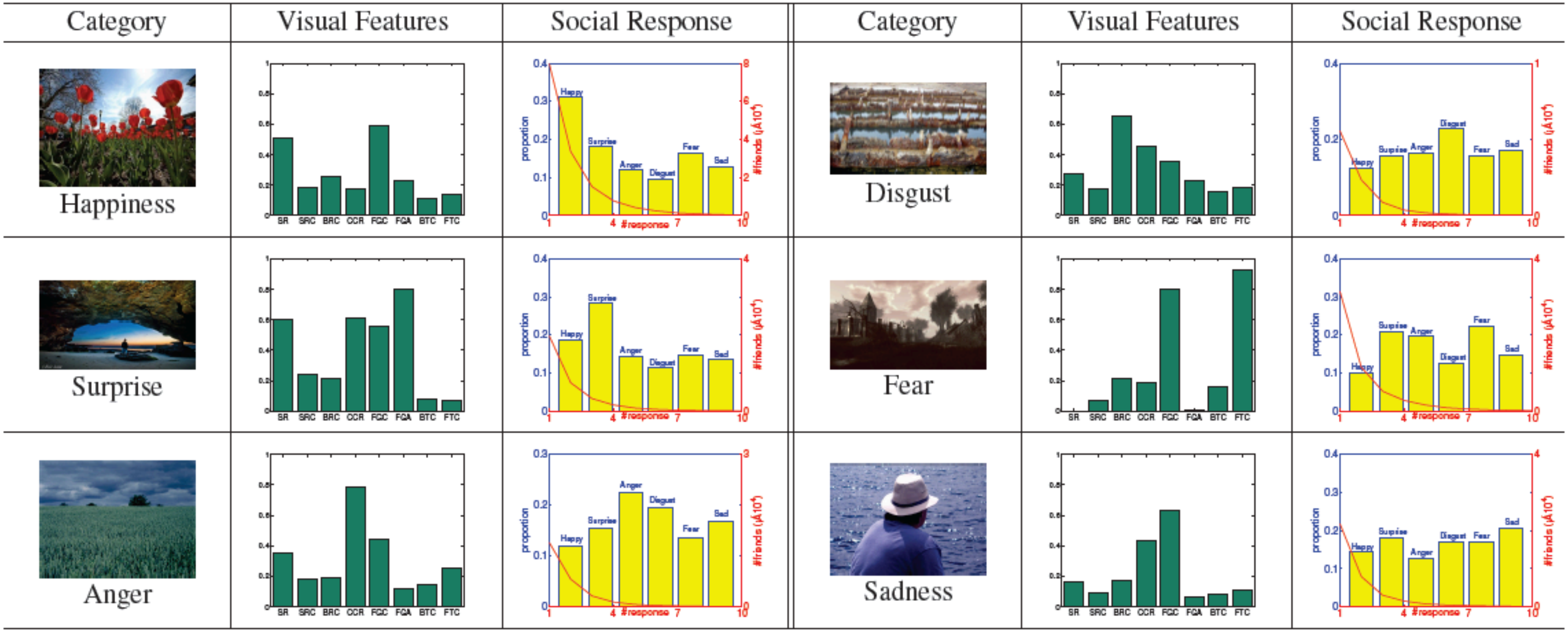


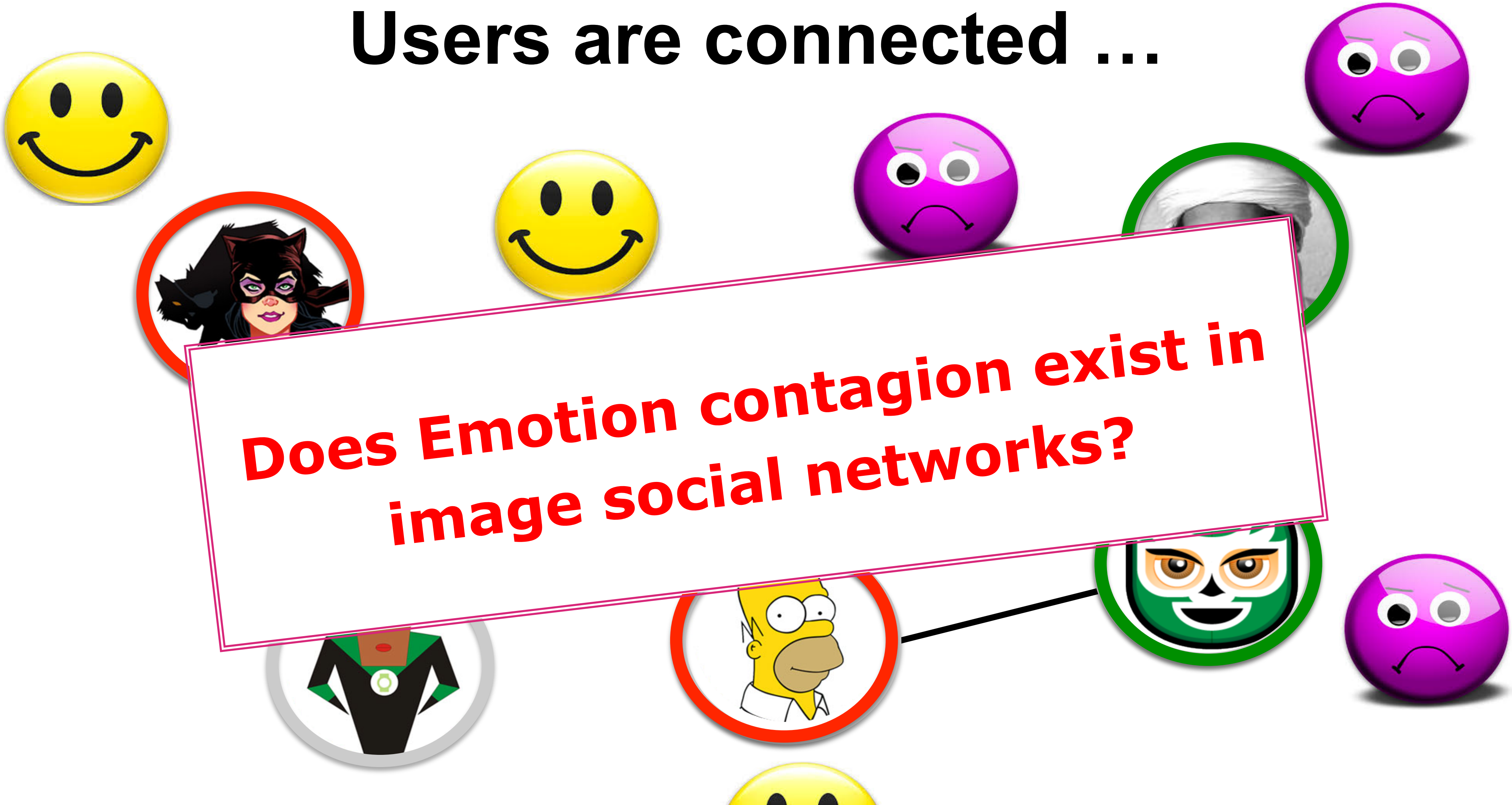
Image Interpretations



- Our model demonstrates how visual features distribute over different emotions. (e.g., images representing Happiness have high saturation)
- Positive emotions attract more response (***+4.4*** times) and more easily to influence others compared with negative emotions.

What will Happen after Spiderman Posts this Photo?

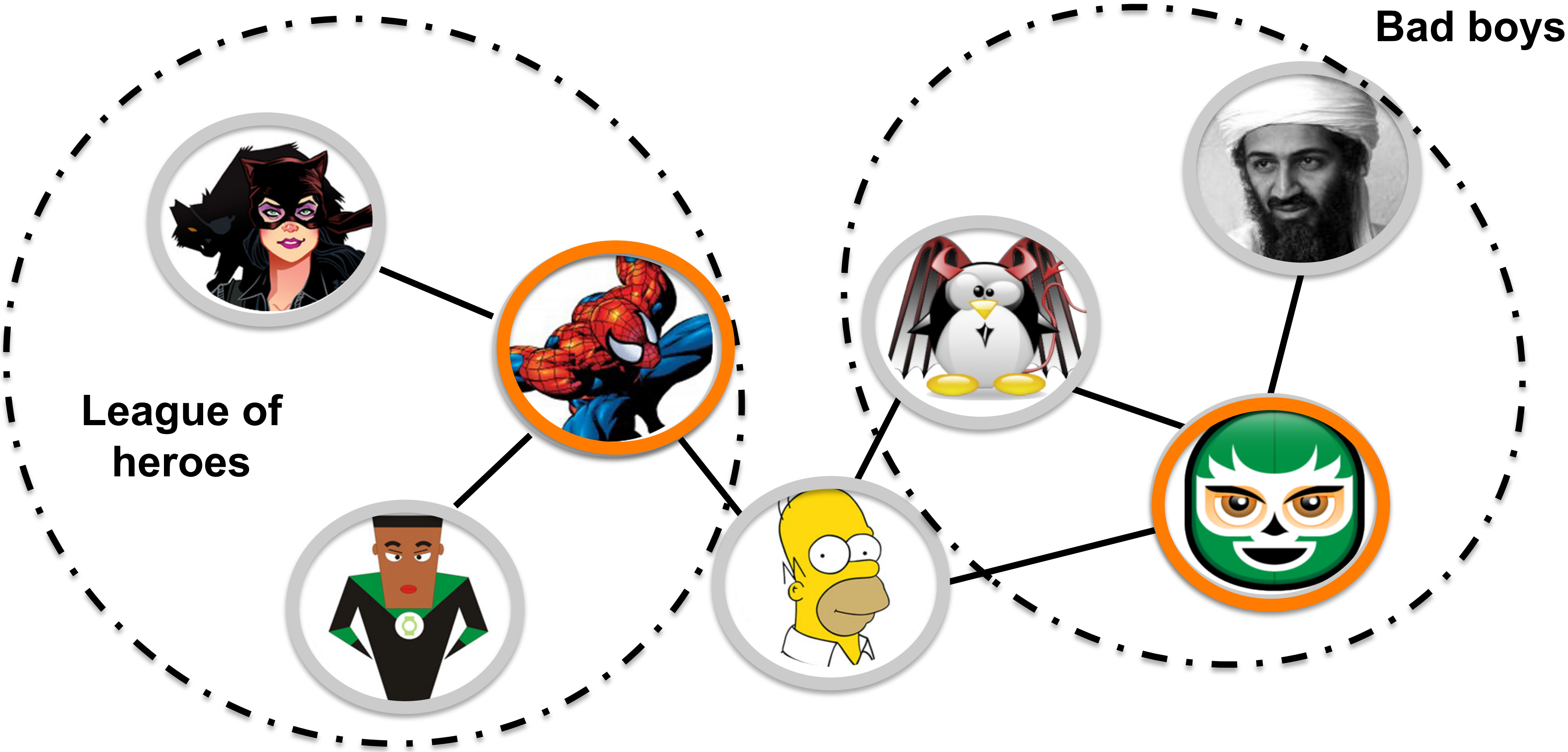
Users are connected …



Does Emotion contagion exist in image social networks?

Emotion Contagion: The cascade of users' emotional statuses influence each other

Social Roles of Users



Opinion leaders: users taking central positions in communities

Social Roles of Users

Will social roles influence emotion contagions?

Structural hole spanners: users bridge otherwise disconnected communities

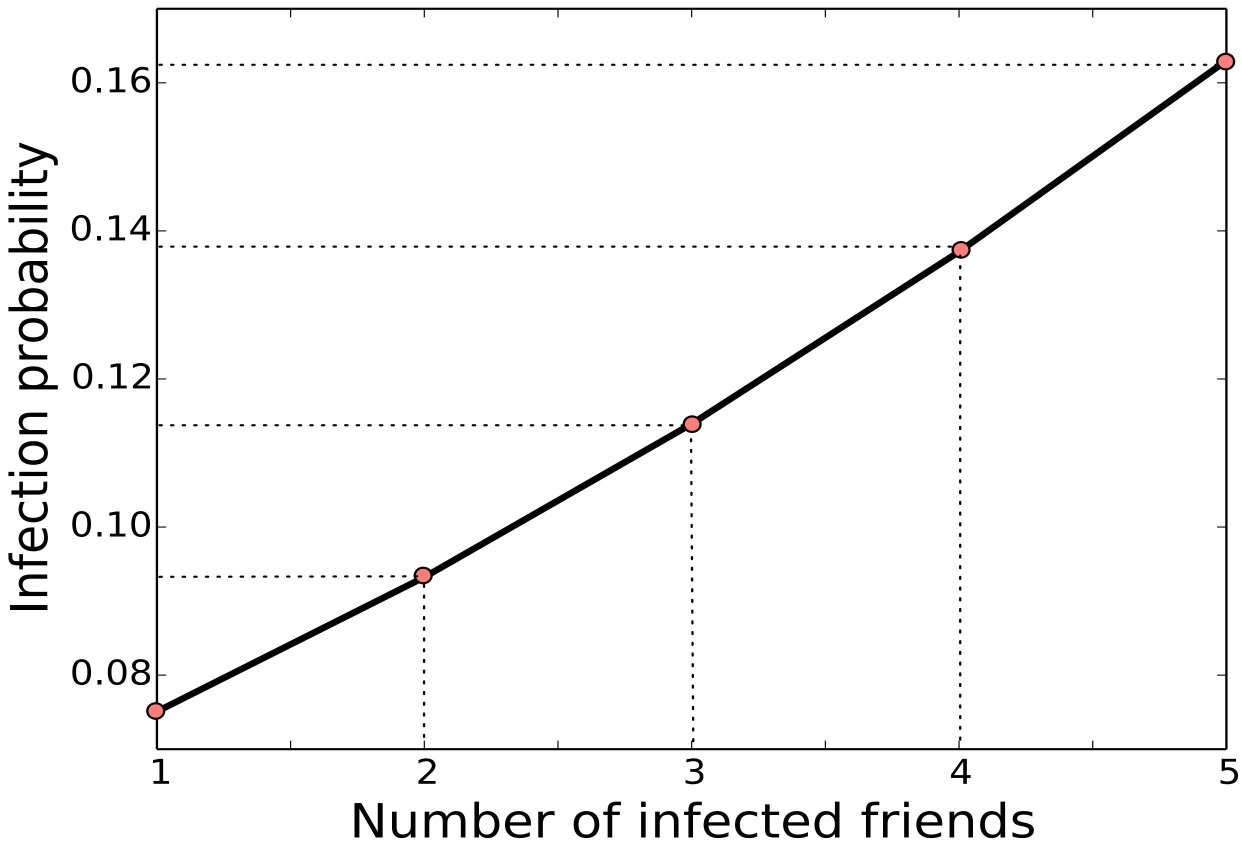
Three Qs to Answer

- **Q1:** Does emotion contagion exist in image social networks?
- **Q2:** Will social roles influence emotion contagion?
- **Q3:** How to better predict the emotional status of users in social networks by considering emotion contagion?

Yang Yang, Jia Jia, Boya Wu, and Jie Tang. **Social Role-Aware Emotion Contagion in Image Social Networks.** AAAI, 2016.

Q1: Existence

Q1.1: When your friends are happy, will you be happy?



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Q1: Existence

Q1.2: When predicting a user's emotional status, will her friends help?

Historical post logs
+
Previous emotion
+
Image features

+
Friends' emotions

Predict

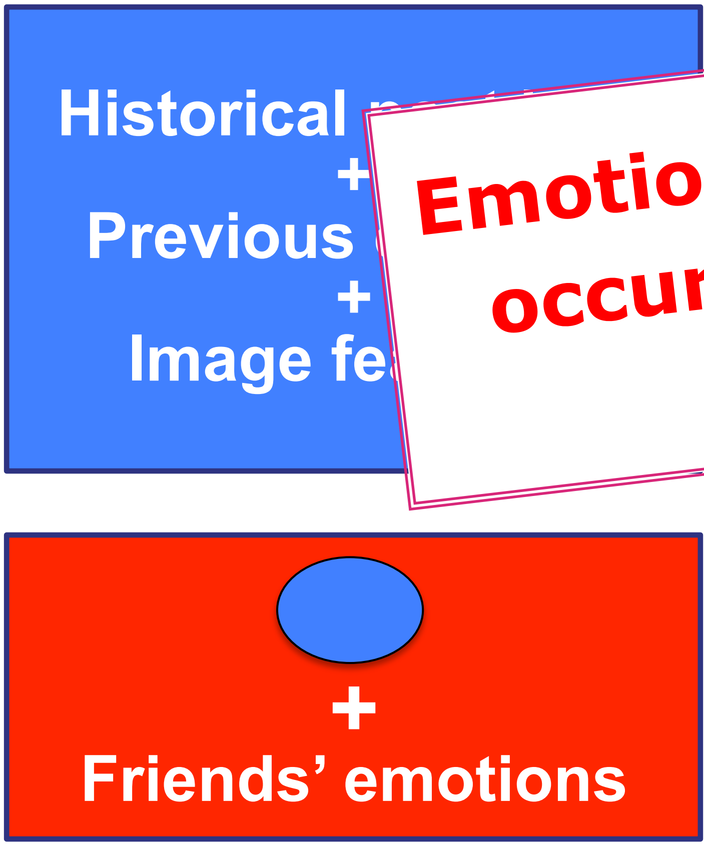
Y_{vt}

User v's emotional status at time t

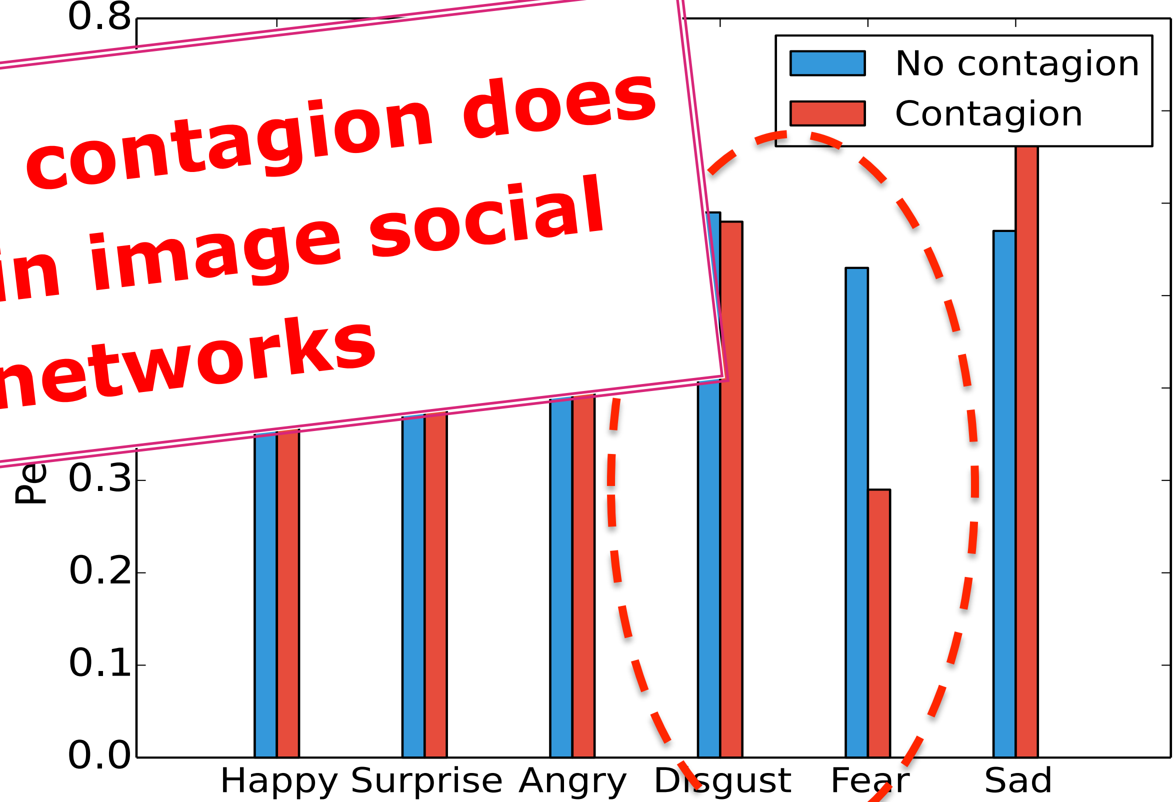
happiness, surprise, anger, disgust, fear, sadness

Q1: Existence

Q1.2: When predicting a user's emotional status, will her friends help?



Emotion contagion does occur in image social networks



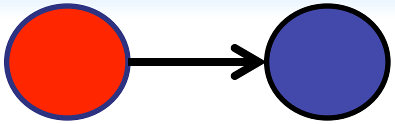
Q2: Social Role

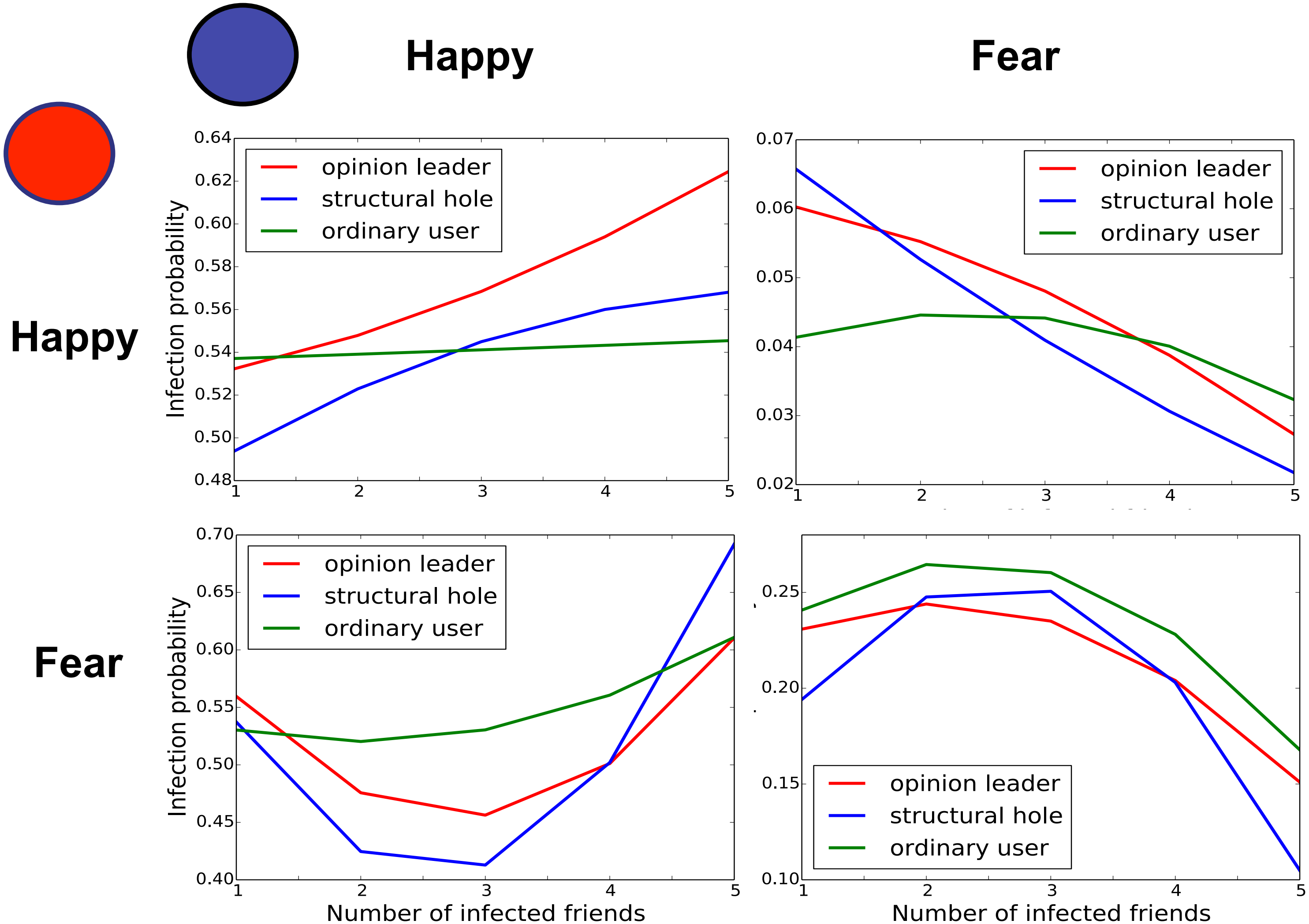
- ***Opinion leaders:*** 20% of users with largest PageRank scores;
- ***Structural hole spanners:*** 20% of users with lowest network constraint scores;
- Others are remaining as ***ordinary users***.

OL and SH ... y users in

Still holds in emotion contagion?

Q2: Social Role

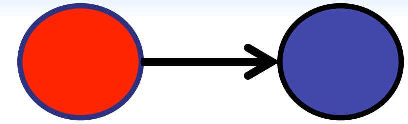




X: number of friends with different social roles.

Y: probability being a certain emotion.

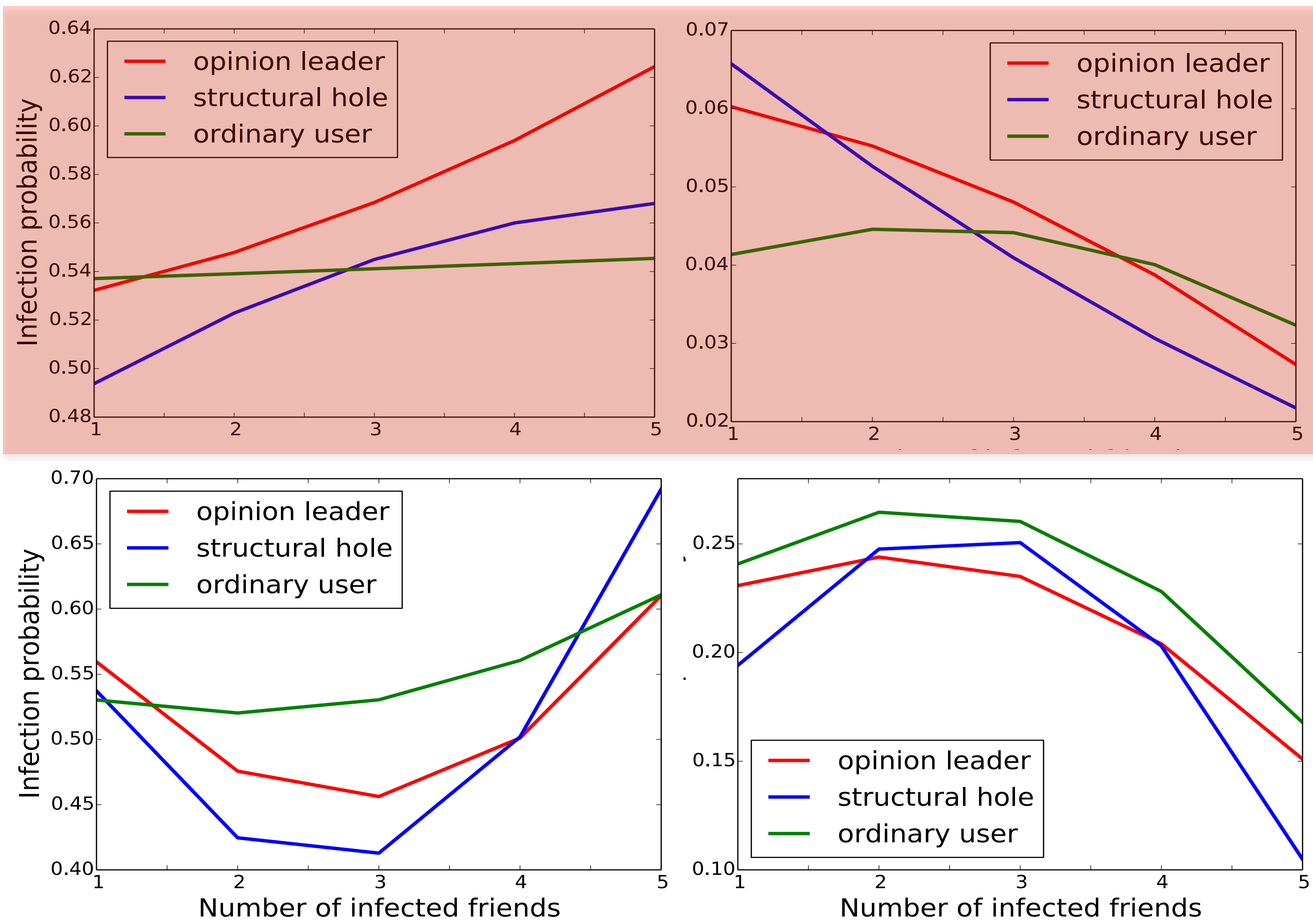
Q2: Social Role



Happy **Fear**

Happy

Fear

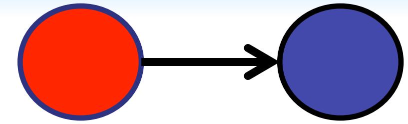


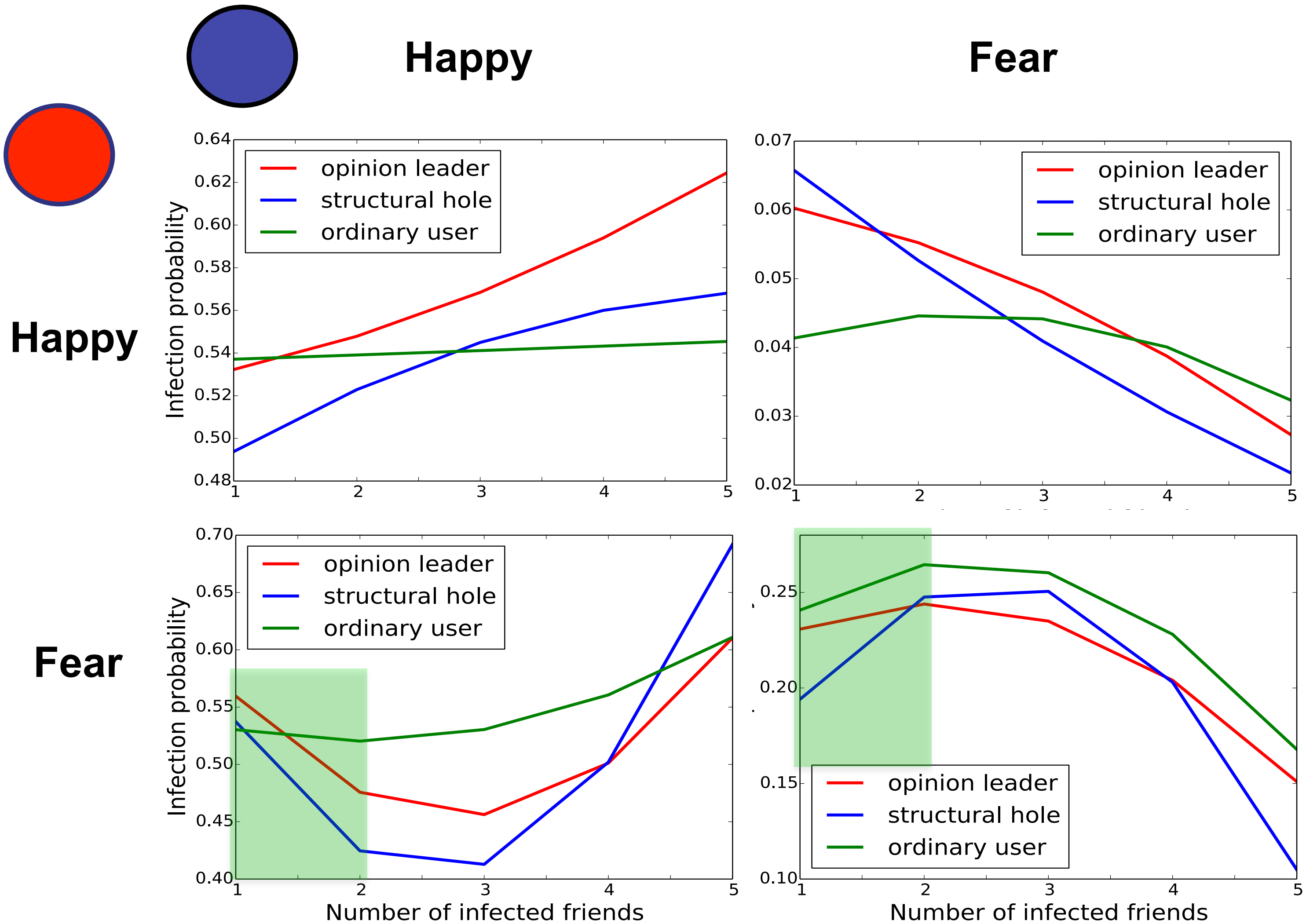
X: number of friends with different social roles.

Y: probability being a certain emotion.

positive emotion delights friends

Q2: Social Role

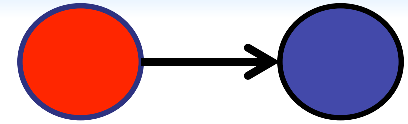


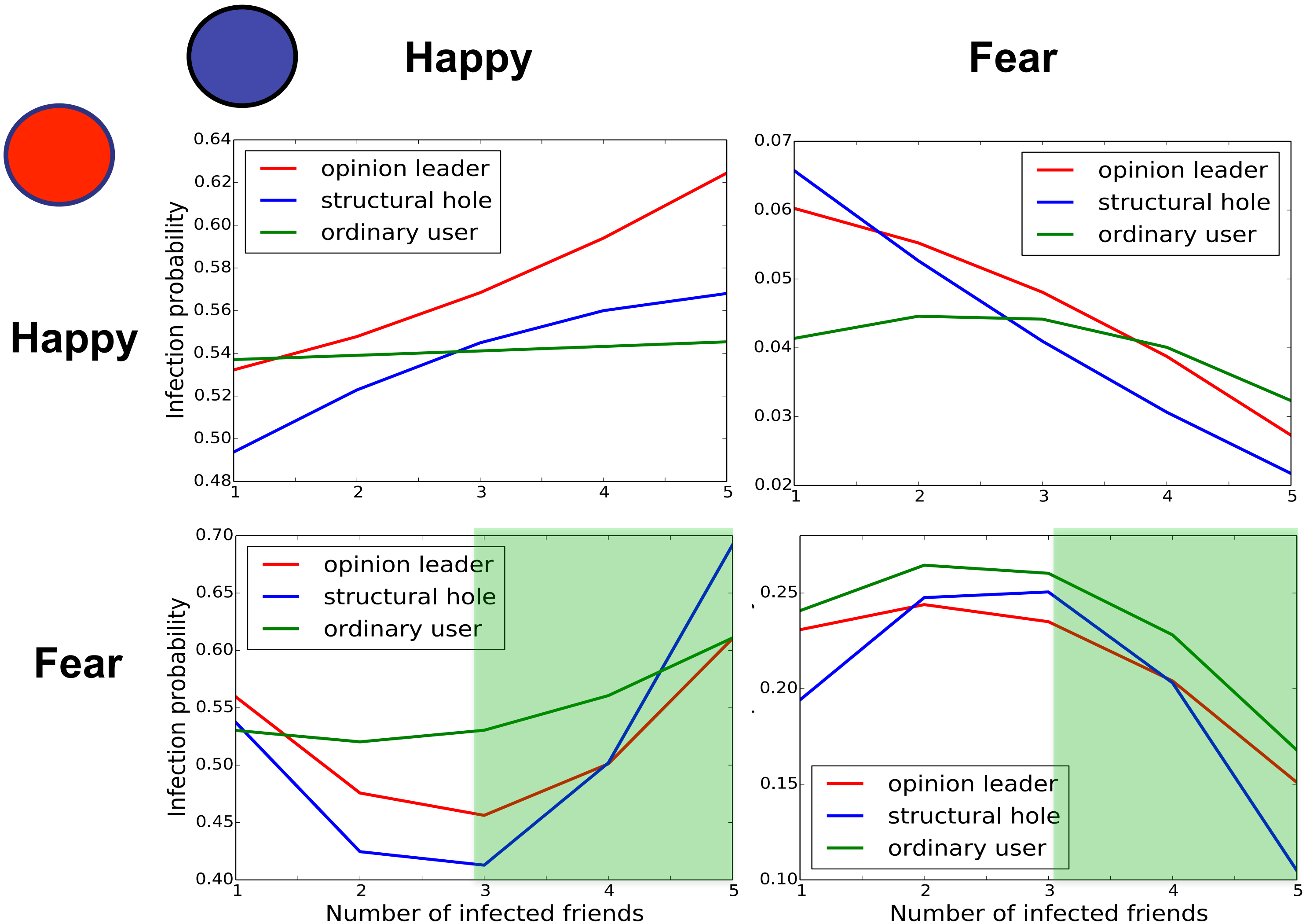


X: number of friends with different social roles.

Y: probability being a certain emotion.

Q2: Social Role



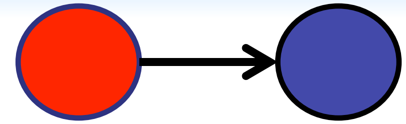


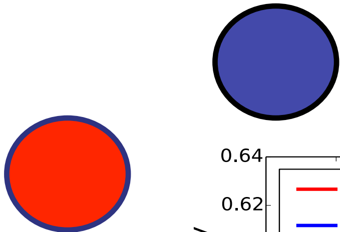
X: number of friends with different social roles.

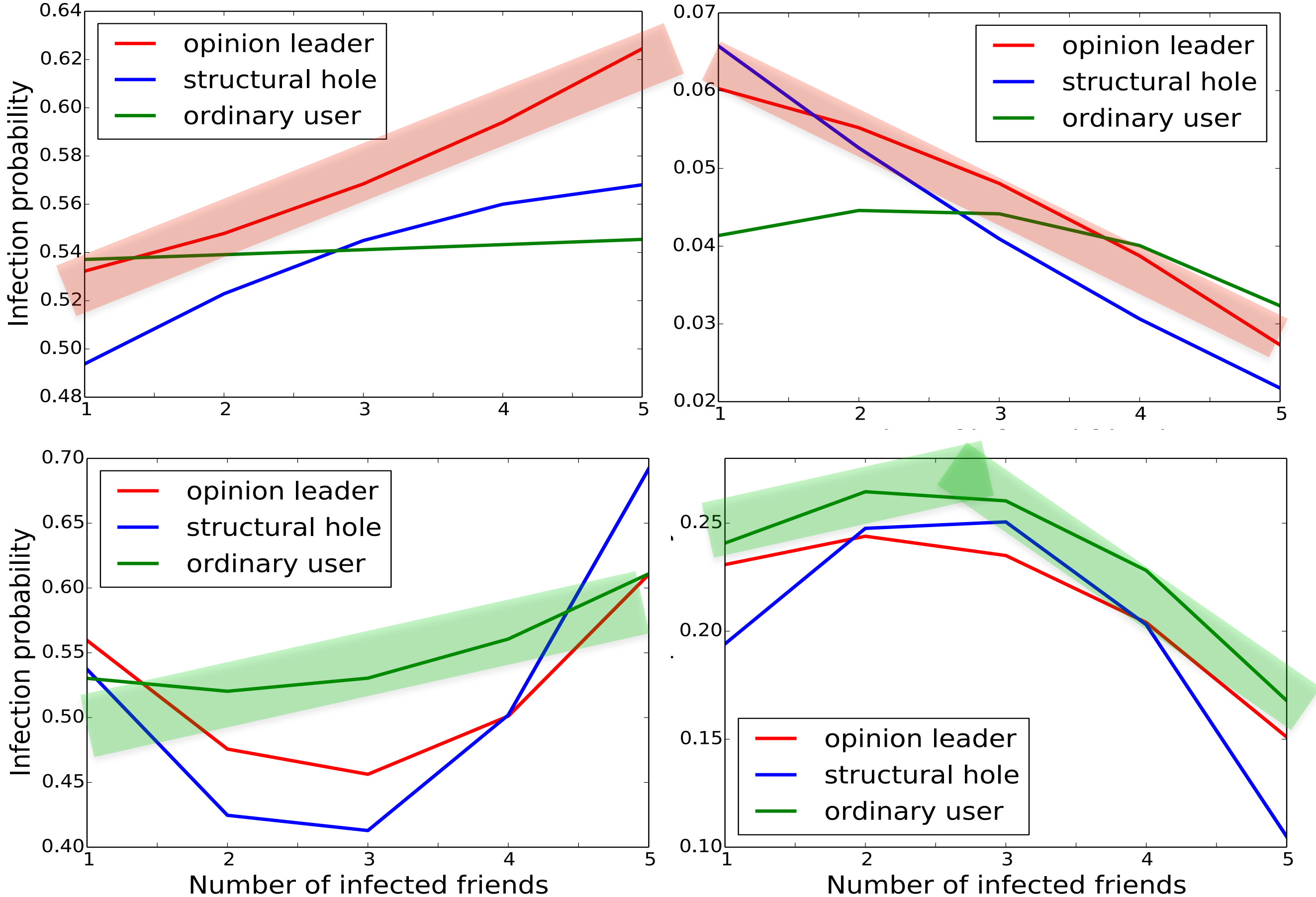
Y: probability being a certain emotion.

"Emotional comfort" phenomena

Q2: Social Role







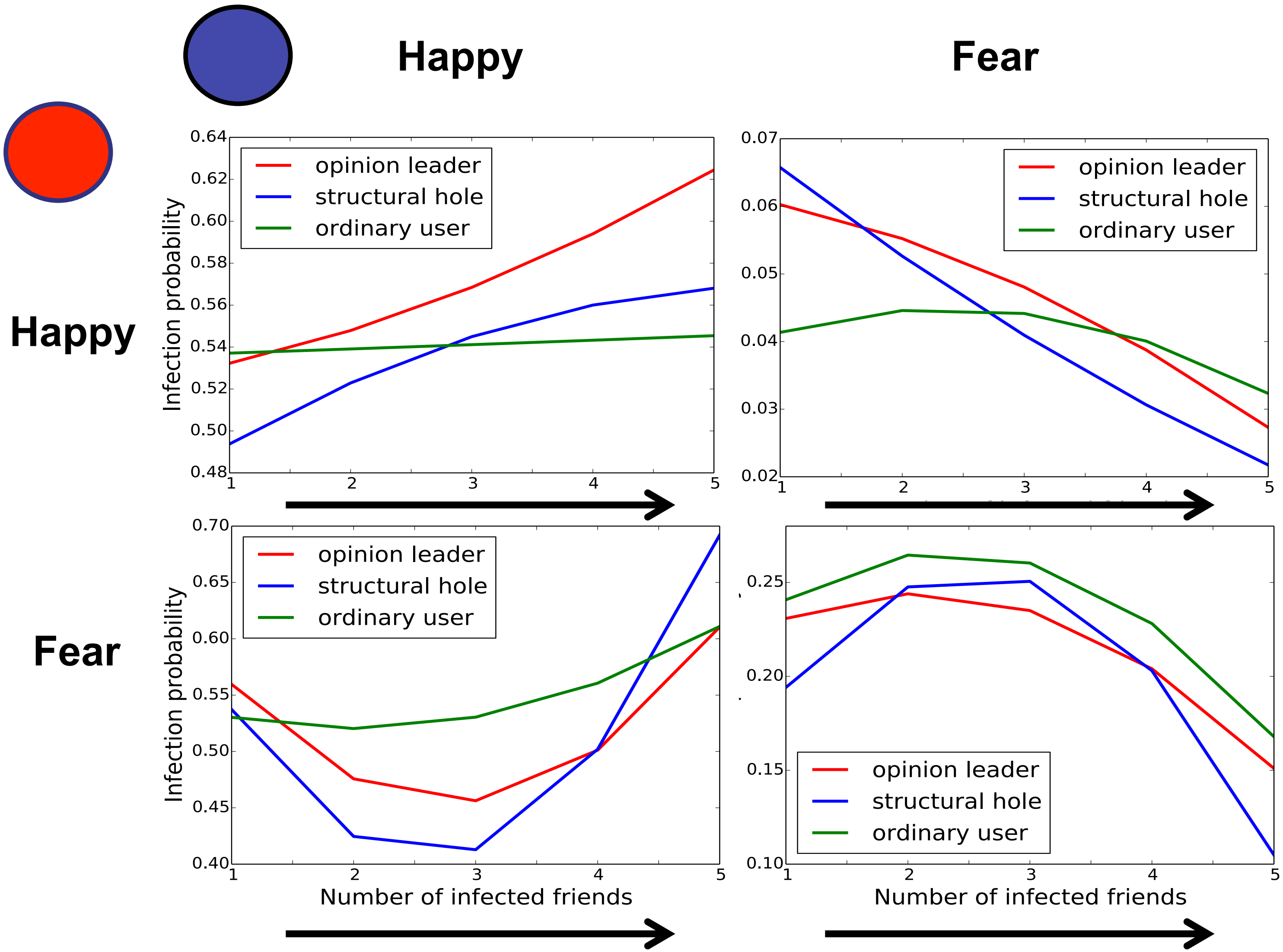
X: number of friends with different social roles.

Y: probability being a certain emotion.

Opinion leaders are more influential on positive emotions

Ordinary users are more influential on negative emotions

Q2: Social Role

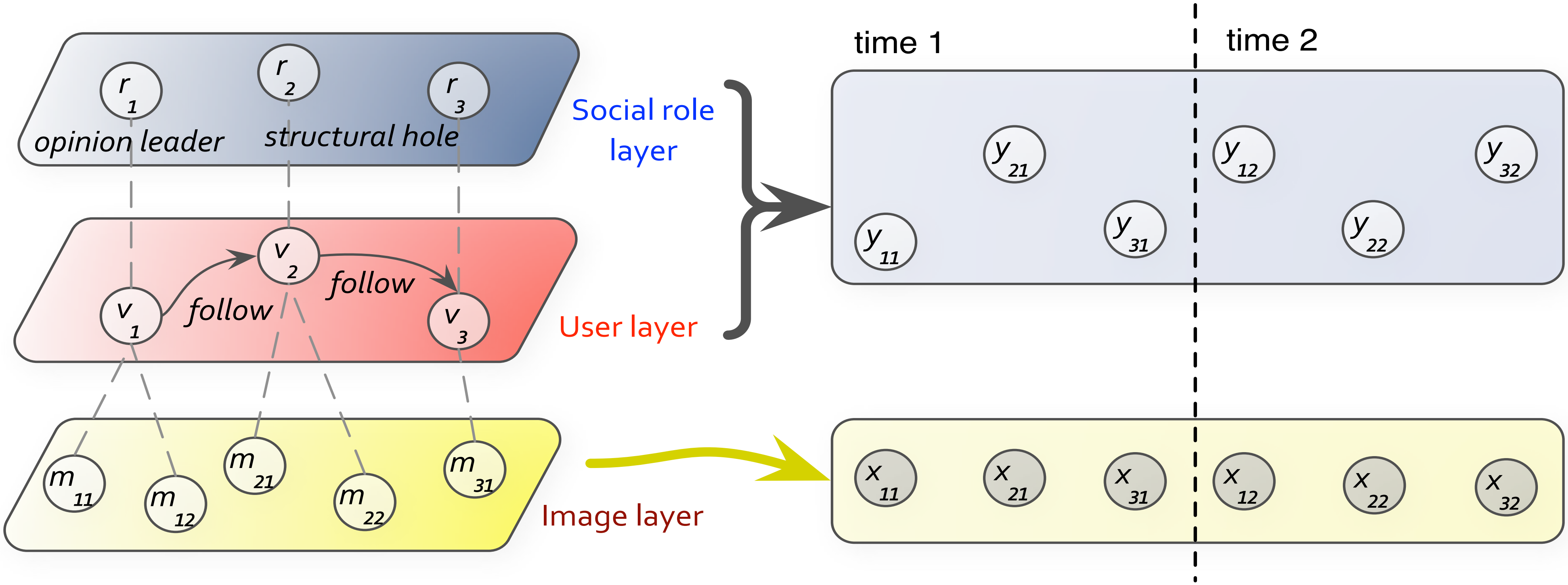


X: number of friends with different social roles.

Y: probability being a certain emotion.

Influence of opinion leaders and structural holes change faster than ordinary users.

Q3: Model



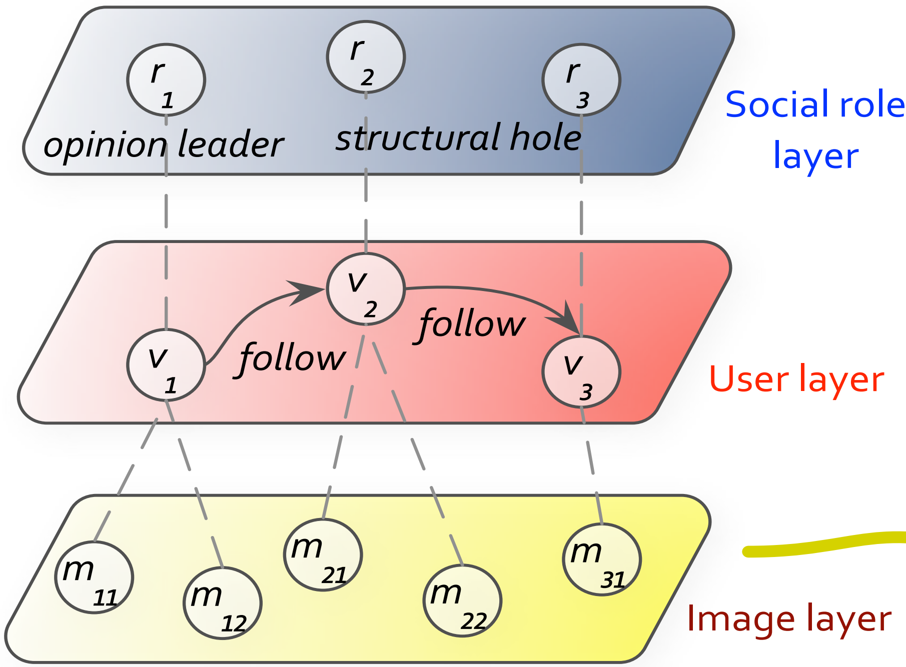
(a) An example of the problem

(b) Social Role-Aware Contagion Model

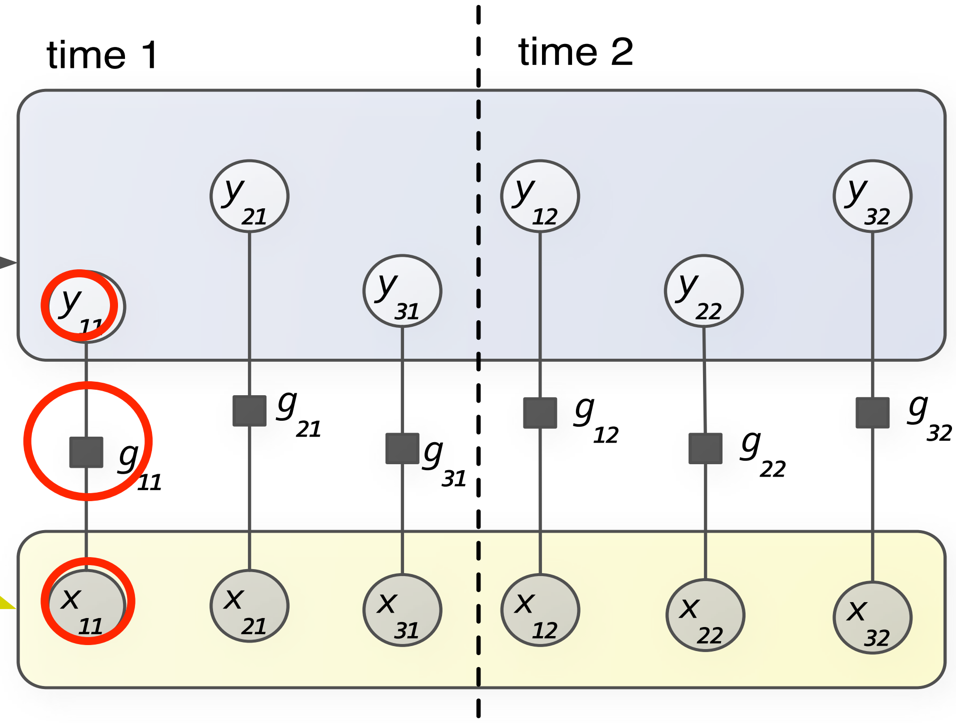
P(Y|G): Conditional probability of users' emotional status given input data

Q3: Model

P(Y|G)=πg(.) …



(a) An example of the problem



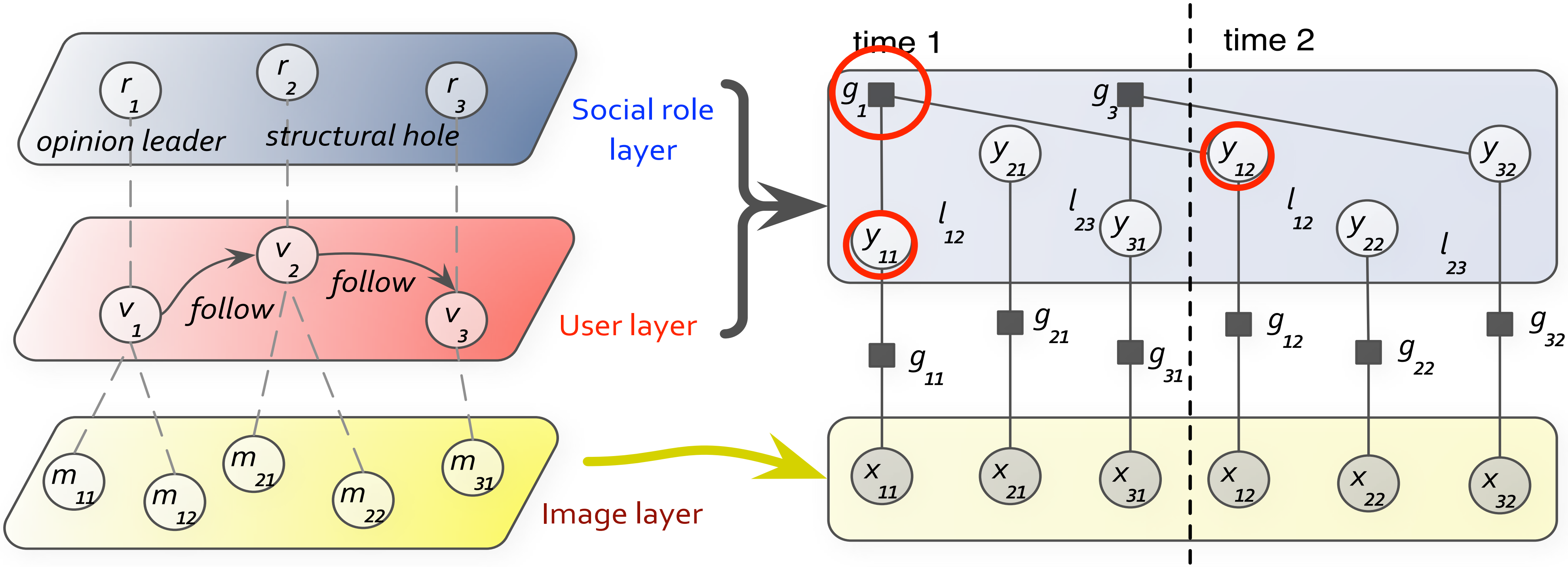
(b) Social Role-Aware Contagion Model

$g(x_{vt}, y_{vt})$: Correlation between v's emotion and the image she posts at t.

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

Q3: Model

P(Y|G)=π{g(.)h(.)} …



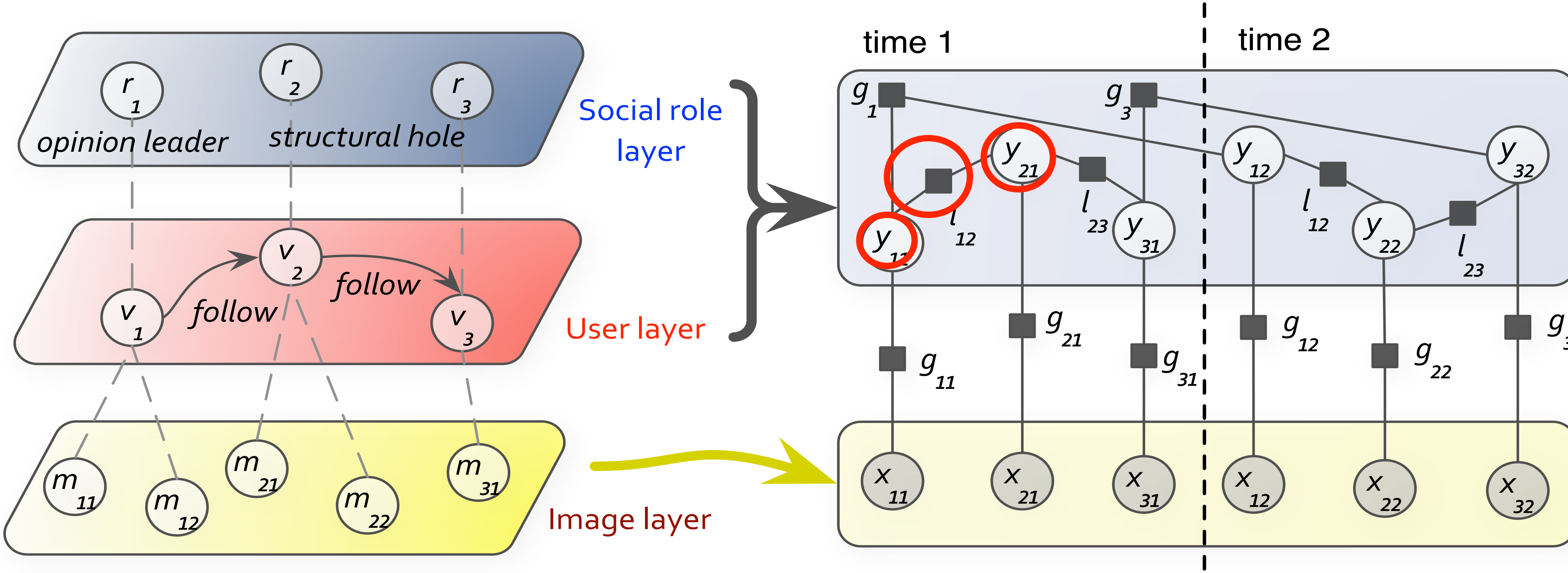
(a) An example of the problem (b) Social Role-Aware Contagion Model

h($y_{ut-t'}$, y_{vt}): Correlation between v's emotion at time t and t-t'.

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

Q3: Model

P(Y|G)=π{g(.)h(.)I(.)}



(a) An example of the problem

(b) Social Role-Aware Contagion Model

$I(y_{ut-1}, y_{vt})$: How v's emotion at t is influenced by her friend u's emotion at t-1.

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

Social role sensitive parameter

Experimental Results

Emotion
Happiness
Surprise
Anger

Flickr dataset:

2,060,353 images, 1,255,478 users
ground truth obtained by user tags

Distribution of users' emotional statuses on Flickr:

happiness: 46.2%
surprise: 9.7%
anger: 8.0%
disgust: 5.3%
fear:17.3%
sadness: 13.5%

Experimental Results

Emotion	Method
Happiness	SVM
	LR
	NB
	BN
	RBF
	CRF
	Role-aware
Surprise	SVM
	LR
	NB
	BN
	RBF
	CRF
	Role-aware
Anger	SVM
	LR
	NB
	BN
	RBF
	CRF
	Role-aware

Baselines

Methods do not consider emotion contagion:
SVM, Logistic Regression (LR),
Naïve Bayes (NB), Bayesian Network (BN),
Gaussian Radial Basis Function Neural Network (RBF).

Methods ignore social role information: CRF

Our model: Role-aware

Experimental Results

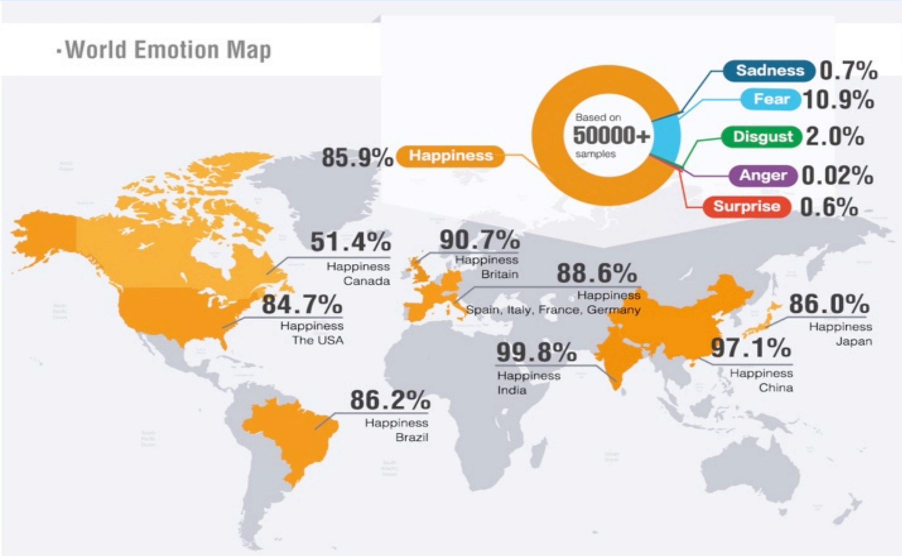
Emotion	Method	Precision	Recall	F1-score	Emotion	Method	Precision	Recall	F1-score
Happiness	SVM								
	LR								
	NB								
	BN								
	RBF								
	CRF								
	Role-aware								
Surprise	SVM								
	LR								
	NB								
	BN								
	RBF								
	CRF								
	Role-aware								
Anger	SVM								
	LR								
	NB								
	BN								
	RBF								
	CRF								
	Role-aware								

Evaluation Metrics:

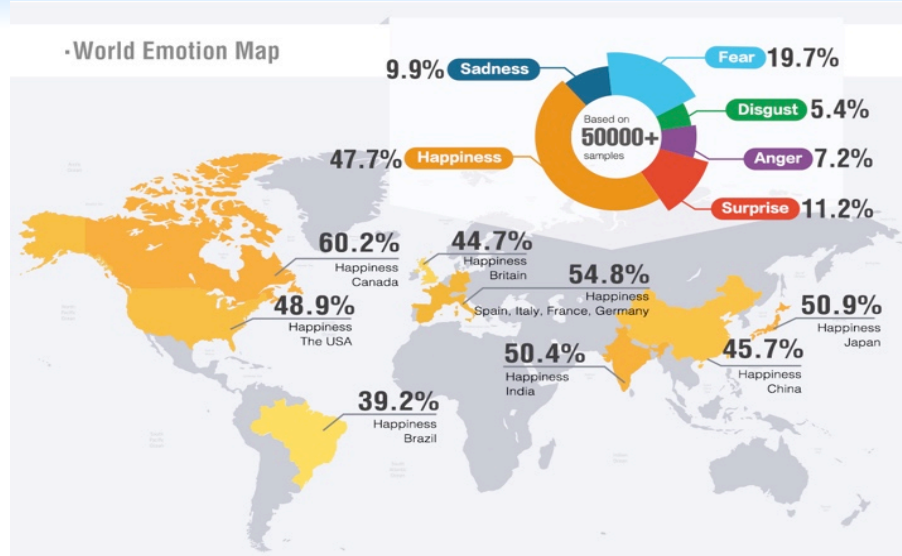
- Precision
- Recall
- F1 Measure

Experimental Results

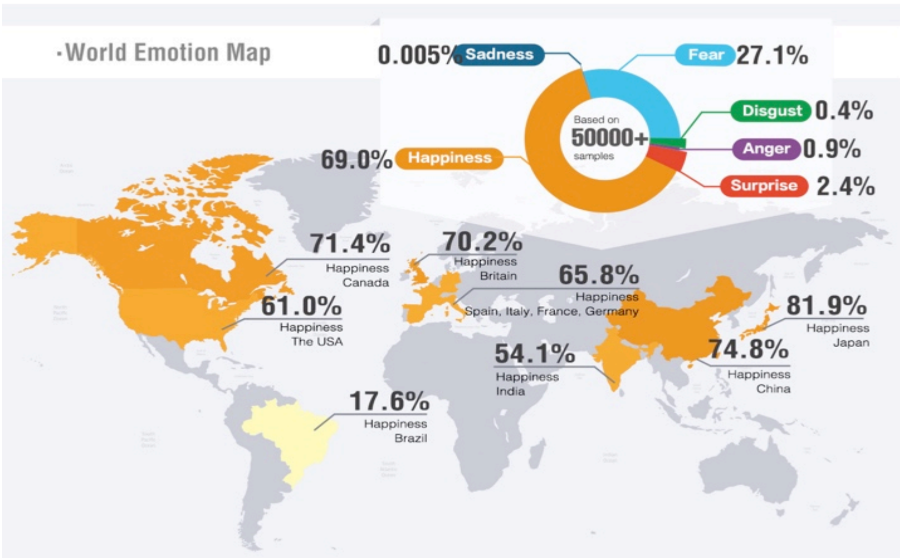
Emotion	Method	Precision	Recall	F1-score	Emotion	Method	Precision	Recall	F1-score
Happiness	SVM	0.5490	0.4682	0.5054	Disgust	SVM	0.5721	0.6223	0.5962
	LR	**0.5726**	0.4234	0.4868		LR	0.5902	0.5847	0.5874
	NB	0.5604	0.4679	0.5100		NB	0.5657	0.7244	0.6353
	BN	0.5605	0.5129	0.5357		BN	0.5666	0.6811	0.6186
	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**
Surprise	SVM	0.5103	0.4821	0.4958	Fear	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
	BN	0.5241	0.4712	0.4963		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**
Anger	SVM	0.5186	0.6371	0.5718	Sadness	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
	BN	0.5260	0.5207	0.5233		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**



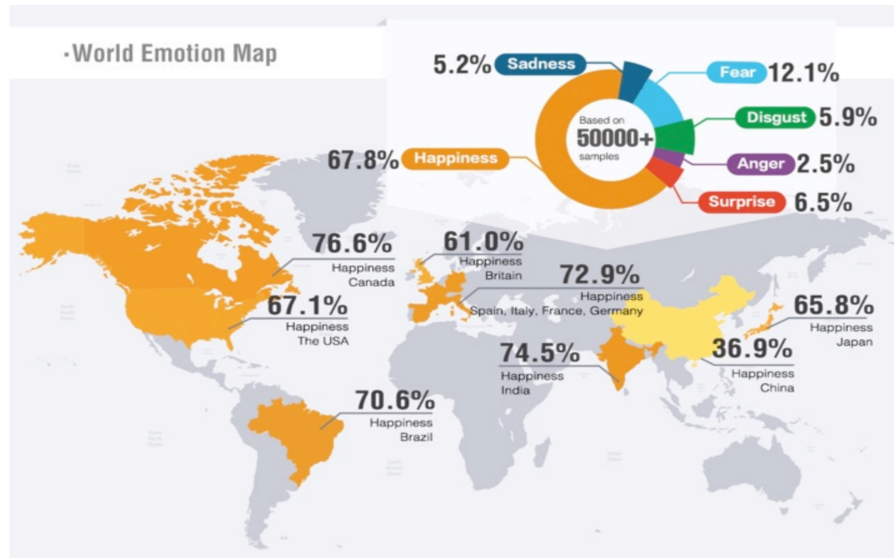
(a) Ground truth



(b) Random users



(c) Opinion leaders



(d) Structural hole spanners