Modeling Emotion Influence Using Attention-based Graph Convolutional Recurrent Network

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ABSTRACT

User emotion modeling is a vital problem of social media analysis. In previous studies, content and topology information of social networks have been considered in emotion modeling tasks, but the inflence of current emotion states of other users was not considered. We define emotion influence as the emotional impact from user's friends in social networks, which is determined by both network structure and node attributes (the features of friends). In this paper, we try to model the emotion influence to help analyze user's emotion. The key challenges to this problem are: 1) how to combine content features and network structures together to model emotion influence; 2) how to selectively focus on the major social network information related to emotion influence. To tackle these challenges, we propose an attention-based graph convolutional recurrent network to bring in emotion influence and content data. Firstly, we use an attention-based graph convolutional network to selectively aggregate the features of the user's friends with specific attention. Then an LSTM model is used to learn user's own content features and emotion influence. The model we proposed is more capable of quantifying the emotion influence in social networks as well as combining them together to analyze the user emotion status. We conduct emotion classification experiments to evaluate the effectiveness of our model on a real world dataset called Sina Weibo[1]. Results show that our model outperforms several state-of-the-art methods.

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CCS CONCEPTS

• **Human-centered computing → Collaborative and social computing**; • **Applied computing → Sociology**; • **Computing methodologies →** *Neural networks.*

KEYWORDS

emotion modeling, social network, graph convolutional network, attention

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1 INTRODUCTION

With the rapid development of social platforms, tweeting on social media has become one of the main ways for people to express their opinions and feelings. By analyzing the heterogeneous content of the tweets, we can infer users' emotion changes over time. It helps us study social dynamics and understand public opinions. At the same time, people's emotions can unconsciously affect the emotions of those around them through online chats [10], which is called emotional contagion [15]. Experiments on Twitter [6] confirmed that users exposed to negative tweets were more likely to post negative content than normal. And other studies on Flickr [2] shown that information dissemination was limited to individuals who were very close to the uploader, and that it took a long time to spread farther. More than 50% of the images were marked as "like" by close friends. [3] analyzed the data of Facebook users and found that each user directly affected the emotion state of about one or two friends by rainfall changes. These studies have proved that there are positive and negative emotion influence in online social networks. So it is reasonable to consider emotion influence as well as content information in emotion modeling tasks.

Previous studies have focused on text, image, user attributes or social network topology to analyze emotion status in social networks. Some [26] inferred emotions from heterogeneous social media data, and others [24] leveraged social network topology in emotion analysis. Besides these

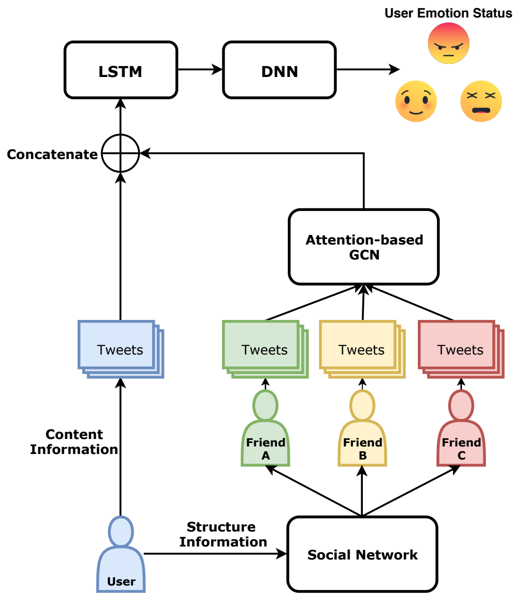


Figure 1: The framework of the attention-based graph convolutional recurrent network.

attributes, we want to further study the emotion inflence of a user's friends at a specific time by analyzing their emotion states.

In this paper, we attempt to model emotion influence in social networks and apply this model to emotion classification tasks in social media platforms. We also want to explore whether different friends have different impacts on users. This problem holds several challenges. The first challenge is to find a reasonable model of emotion influence which can handle both structure and content information of the social network. Secondly we should find a way to distinguish the different influence level of friends and focus on those who have greater influence.

To address these challenges, we propose an attention-based graph convolutional recurrent network (GCRN). The main framework is illustrated in Figure 1. For each user at a specific time t, we can extract tweets posted a short period of time before t from the local neighborhood. An auto-encoder model is used to learn a joint representation of both text and image information of these tweets. Then the attention-based graph convolutional network aggregates content features in the neighborhood with different weights defined by the attention layer. It gets the representation of emotion influence. After that the LSTM network learns user's personalized content features and emotion influence together.

Our contributions are listed as follows:

- We confirm the existence of emotion influence in the social network and propose a GCRN model to model user's emotion state from both personal content and emotion influence.
- We use attention mechanism in the proposed model to differentiate emotion influence between friends.
- We propose an attention-based GCRN to model emotion influence, and conduct emotion classification experiments on Sina Weibo dataset to analyze its performace. Our model outperforms several state-of-the-art methods in terms of F1-measure.

2 RELATED WORK

Emotion analysis in social networks

In the existing literature, a bunch of methods targeting on emotion analysis in social networks have been proposed. These studies mainly use the content information [12, 19, 27] and social role [23, 24] to determine user's emotion status, but the combination of content and social influence may contain more information of user's emotion status.

Another strand of literature focuses on the influence and correlation in social networks. [18] demonstrated that the higher the frequency of communication in the instant messaging network, the stronger the similarity of interests and personal characteristics. [21] found three factors that can affect user's emotion: the user's behavior, the previous emotional state and the influence of social relations. [20] pointed out that there were some special nodes in the social network (such as structural holes, opinion leaders, etc.) that have greater influence to others than ordinary users. Different from these studies, we focus on the influence specifically on emotions, which is less conscious and more personal. Compared with social status, the intimacy between friends can be more important.

Some studies have already proved that social influence is related to network structures. [25] proposed an emotion mining method from text, which can be used to predict the strength of the relationship between users. [5] pointed out that different emotions had different correlation rate. They also found that the interaction frequency and the number of friends can affect the influence level. [7] designed a probabilistic model of the effects of multiple users, and calculated probability values by analyzing social relationships and user behavior in social networks. Different from these studies, we focus on both structure and content information in the social network to better determine user's current emotion status.

Graph convolutional network

Many scholars have studied the method of modeling spatio-temporal sequences using graph convolutional networks and recurrent networks.

The graph convolutional network is proposed to generate node representations in networks [9]. Node features are learned by sampling and aggregating feature information (such as text attributes) in the local neighborhood of the node [8]. Besides mean aggregation and max pooling, attention mechanism is also introduced in graph convolutional networks [22].

In order to learn spatial correlation in input data, [17] proposed a convolutional LSTM network (convLSTM) to learn spatial correlation in input data using two-dimensional grid convolution. Then the convolution operation is extended to topological graphs by the graph convolutional recurrent network [16], while others [13] further solved the problem of topological graph changing with time.

For our problem, we incorporate the graph convolutional recurrent network with attention mechanism to aggregate features from other users in the social network. The attention weights learned by the model can reflect the influence level of different users in the neighborhood.

3 PROBLEM DEFINITION

Information on social media contains two parts: tweets K and social network $G = (V, E)$, where V represents the users and $E \subseteq (V \times V)$ is the set of connections. Specially, every $e_{ij} \in E$ in Sina Weibo is a directed edge which points from v_i (the follower) to v_j (the followee). Given a user $v \in V$ and his tweets in K, content features are organized in time sequences as $X_v = (\dots, x_{v,t_{i-1}}, x_{v,t_i}, x_{v,t_{i+1}}, \dots)$, where i represents the posted time order of every tweet and x_{v,t_i} represents the features of the tweet.

Definition 1. A heterogeneous social network is a directed graph $G = (V, E, K, Y)$, where V is the set of users, $e_{ij} \in E$ denotes that user v_i follows user v_j, $k_i^t \in K$ denotes the tweet posted by user v_i at time t. Y_i^t denotes the emotion status of user v at time t.

Definition 2. The neighborhood of user v_i is the set of users V_i that can reach him in a given step number k. Given the adjacency matrix A, let $A_k = \sum_{i=0}^{k} A^i$. If $A_k(i, j) \neq 0$, we can consider user $v_j \in V_i$, which means the emotion of v_j may affect v_i.

Problem. Our problem is to integrate users' content information and emotion influence into emotion status understanding. Given a user v in G, a specific time t, and the historic emotion status before t, our goal is to analyze the emotion status of v at time t:

$$f : G = (V, E, K, Y_0, \dots, Y^{t-1}) \rightarrow Y^t. \tag{1}$$

4 DATA OBSERVATION

The existence of emotion influence

In order to study emotion influence in social networks, we first need to verify its existence.

We randomly select 2000 pairs of users from the data set, which belongs to two groups: a friend-related group (in which user v_1 follows user v_2) and a friend-independent group (in which the two users are not linked). We define the emotion similarity as the ratio that user v_1 has the same emotion as user v_2 within a short period of time.

$$P(v_1, v_2) = \frac{\sum_{i \in K_1} \sum_{j \in K_2 \land Y_i = Y_j} R(t_i - t_j)}{\sum_{i \in K_1} \sum_{j \in K_2} R(t_i - t_j)}, \tag{2}$$

where $R(\Delta t) = 1$ if $\Delta t < T$. It determines whether the emotions are relevant since emotion influence is time-sensitive.

The friend-related group has a higher emotion similarity (27.1%) than the friend-independent group (20.7%). The results confirm that users are more likely to have same emotion experience as their friends, which means user's emotion is actually influenced by his or her friends.

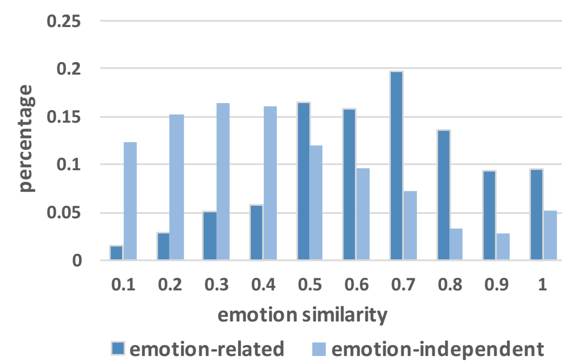


Figure 2: The distribution of emotion similarity. X-axis refers to the emotion similarity calculated by Equation 2. Y-axis refers to the percentage of friend pairs.

For the same user, the emotion of different friends may have different impact. For example, if a friend has same interests with the user, the impact may be relatively high.

If two friends have had similar emotional expressions in the past, it is reasonable to assume that they may maintain this similarity in the future. We choose 1000 friend pairs from the dataset who often post tweets together. In particular, if v_1 follows v_2, then v_2 has more than 50% of the blogs posted within a short time period (3 days) of v_1. The pairs are divided into two groups, the emotion-related group and the emotion-independent group by the average emotion similarity in the first three month (over or under 50%). We use Equation 2 to measure the influence level between two users. Then we calculate the distribution of emotion similarity of the two groups in the next two months.

As shown in Figure 2, friends in the emotion-related group are more likely to have higher emotion similarity than those in the emotion-independent group.

Summary: The results of above case studies confirm that a user's emotion is actually influenced by his or her friends, and the emotion similarity between them is rather stable over time. So it is reasonable to introduce emotion influence into emotion analysis and selectively focus on friends who have greater influence on users. And if we can better characterize the emotion influence with content as well as structure information, we can have better understanding of user's emotion status.

The persistence of user's emotion

In order to find out if the emotion from the past can affect current status, we calculate the probability of users changing from one specific emotion to different emotions.

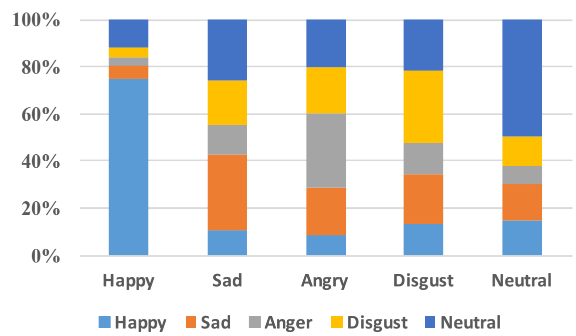


Figure 3: The probability of emotional transition. Each bar shows the probability of a specific emotion of one user transforms to another.

It can be seen in Figure 3 that the probability of one emotion transforms to itself is the highest in every category (43.7% on average), which means the users are more likely to maintain their previous emotion status. So it is useful to take into account the previous state of users.

5 METHODOLOGY

In this section, we will introduce our proposed model, attention-based graph convolutional recurrent network in detail. We first introduce the general framework of our method, and then the main components such as graph convolutional recurrent network, attention mechanism and auto-encoder.

Framework

In our problem, the tweets posted by users in the social network can be seen as spatio-temporal sequences. Each user posts a series of tweets in order of time and the tweets posted by different users at a point in time can affect each other.

We use a graph convolutional recurrent network to integrate user's personal content and social relations. The framework is shown in Figure 1. Firstly we train an auto-encoder to get joint representations of text and images in all tweets and deal with the problem of modality deficiency. Then we use an attention-based graph convolutional network to learn the emotion influence by aggregating features from the user's friends in a short time period. The attention mechanism is used to focus on friends who have greater contribution on emotion influence. Finally, LSTM is used to learn users' emotion status from their personal content and emotion influence.

Pre-training: auto-encoder

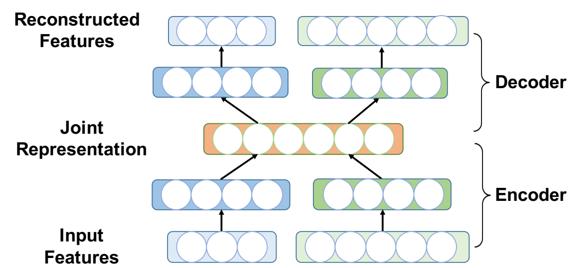


Figure 4: The structure of the auto-encoder.

We design an auto-encoder model to learn a joint representation of image and text for future processing. The structure is shown in figure 4. The input features $X = (X_1, \dots, X_n)$ contain n modalities $X_i = (x_1, \dots, x_{d_i})$ with different dimentions. We first extend the features of each modality X_i to $Y_i = (y_1, \dots, y_d)$ with the same input dimention d:

$$y_k = \sigma(\sum_{x_j \in X_i} w_{ikj} x_j + b_{ik}), \quad (3)$$

where w_i is the weight matrixs, b_i is the bias and σ is the activation function.

Then we learn the joint representation $S = (s_1, \dots, s_k)$ and the reconstructed features $\hat{Y}$ from the concatenation of modalities $Y = (Y_1, \dots, Y_n) = (y_1, \dots, y_{nd})$ as:

$$\begin{aligned} s_i &= \sigma(\sum_{y_j \in Y} w_{ij} y_j + b_i) \\ \hat{y_i} &= \hat{\sigma}(\sum_{s_j \in S} \hat{w_{ij}} s_j + \hat{b_i}). \end{aligned} \quad (4)$$

Then we can get the reconstructed input features $\hat{X} = (\hat{X_1}, \dots, \hat{X_n})$. For each $\hat{X_i}$,

$$\hat{x_k} = \hat{\sigma}(\sum_{y_j \in Y_i} \hat{w_{ikj}} y_j + \hat{b_i}). \quad (5)$$

$w, \hat{w}$ are the weight matrixs, $b, \hat{b}$ are the bias and $\sigma, \hat{\sigma}$ are the activation functions.

The loss of the auto-encoder is calculated as the mean squared error of the input feature X and the reconstructed output $\hat{X}$. We train this model with unlabeled data first. Then we use the encoder part to get the joint representation S of text and image features when training the GCRN model.

Graph convolutional recurrent network

In other areas, graph convolutional network has been used to handle graph-structured data. The model could obtain the feature representation of local network structure and the content in the topological graph. On this basis, [16] proposed graph convolution recurrent networks to model spatio-temporal sequences.

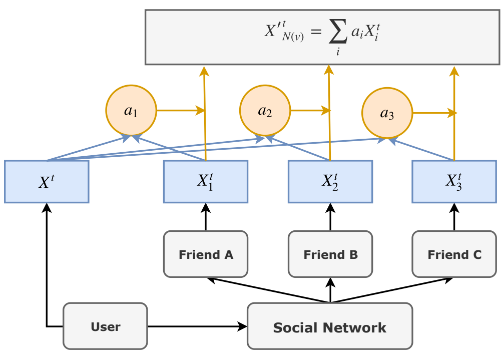


Figure 5: The structure of the attention-based graph convolutional network.

In our model, the graph convolutional recurrent network is used to combine content features and emotion influence. aggregate content features from friends who have emotion influence on the user. The social network in Sina Weibo is a directed graph. If user v follows user u, it means user v is interested in what user u has posted and can be influenced by u. For user v in the social network, we consider all users v can reach within K-hops as the neighborhood $N(v)$, where K controls the size of the neighborhood. We calculate the emotion influence feature $x'^{t}_{N(v)}$ as the weighted sum of the features of all friends in the neighborhood who have posted tweets in a short time period before t,

$$x'^{t}_{N(v)} = \sum_{u \in N(v)} \alpha_{uv} x^{t'}_{u}, \tag{6}$$

where $t' \in [t - \Delta t, t]$. α_{uv} is the weight defined by the attention mechanism.

Then the new representation x'^{t}_{v} is considered as the concatenation of user's personal content features and the emotion influence features.

$$x'^{t}_{v} = concat(x^t_v, x'^{t}_{N(v)}). \tag{7}$$

Then LSTM is used to learn the user's behaviour from aggregated input features. Compared with other neural networks, LSTM considers each user's tweets as a sequence of dynamic changes over time, which can better explore the user's characteristics.

The LSTM network takes the aggregated feature sequence $x'_v = (x'^{0}_{v}, \ldots, x'^{T-1}_{v}, x'^{T}_{v})$ as input, where v is the user, T is the length of time steps. At timestep t, the LSTM unit takes the operations in Equation 8.

$$\begin{aligned}
i_t &= \sigma(W_{ii}x'_t + b_{ii} + W_{hi}h_{(t-1)} + b_{hi}) \\
f_t &= \sigma(W_{if}x'_t + bif + W_{hf}h_{(t-1)} + b_{hf}) \\
g_t &= tanh(W_{ig}x'_t + b_{ig} + W_{hg}h_{(t-1)} + b_{hg}) \\
o_t &= \sigma(W_{io}x'_t + bio + W_{ho}h_{(t-1)} + b_{ho}) \\
c_t &= f_t c_{(t-1)} + i_t g_t \\
h_t &= o_t tanh(c_t).
\end{aligned} \tag{8}$$

Finally the classifier gets user's emotion status from the output sequence $h_v = (h^0_v, \ldots, h^{T-1}_v, h^T_v)$ of LSTM.

$$y^t_v = \sigma(Wh_t + b), \tag{9}$$

where W is the weight matrix, b is the bias and σ is the activation function.

Attention mechanism

The attention weight α_{uv} shows the contribution of user u's features to user v at time t. It helps us selectively focus on those features that best reflect the emotion status of the user v. α_{uv} is defined as the softmax of the attention coefficients of all friends in the neighborhood of user v.

$$\alpha_{uv} = softmax(e_{uv}) = \frac{\exp(e_{uv})}{\sum_{i \in N(v)} \exp(e_{iv})}. \tag{10}$$

A personalized attention parameter $a_v \in R^{2d}$ is used to compute the attention coefficients, where d is the dimension of the content feature.

$$e_{uv} = a_v \cdot concat(x^t_v, x^{t'}_u). \tag{11}$$

6 EXPERIMENTS

In this section, we conduct experiments using Sina Weibo dataset to evaluate the performance of our model and the contribution of the components.

Experimental setup

Data collection. The data used in our experiments are from Sina Weibo. We downloaded tweets from May 2011 to June 2012, as well as the rations between users.

For a large-scale dataset, it is unrealistic to manually mark the emotion labels of each tweet. So we adopt the emotion

Table 1: The F1-measure of all methods

Method	Happy	Sad	Angry	Disgust	Neutral	F1-macro	F1-micro
DNN	0.599	0.301	0.474	0.336	0.448	0.431	0.482
LSTM	0.846	0.385	0.482	0.377	0.565	0.531	0.585
GCN(GraphSAGE)	0.831	0.316	0.493	0.366	0.573	0.516	0.592
GCN-attention	0.823	0.389	0.504	0.388	0.572	0.535	0.596
GCRN	0.888	0.405	0.525	0.404	**0.603**	0.565	0.629
GCRN-attention	**0.902**	**0.421**	**0.540**	**0.422**	0.600	**0.577**	**0.632**

tagging method, which is widely used in emotion classification problem. We consider the descriptions of emoticons(which is defined by Sina Weibo) in tweets as the standard of users' emotions. We use the emotion word lists defined by Wordnet [14] based on synonyms to divide the descriptions into five emotion categories: happy, sad, angry, disgust and neutral. These emotions are selected from Paul Ekman's basic emotions [4] and the emoticons belonging to them are most frequently used. Then we remove tweets with emoticons belonging to more than one category.

Finally, we select 1,789,417 tweets from the dataset (437,750 for happiness, 356,661 for sadness, 280,726 for anger, 304,756 for disgust and 409,524 for neutral). These tweets belong to 52,382 users. Each user posted 34.2 tweets on average. We take the tweets posted in first 70% of the time period for training, the next 10% for validation and the last 20% for testing.

Feature extraction. For text features, we first remove special symbols, numbers and other stop words from the text. Then we use the Paragraph Vector [11] to convert it to 100-dimensional feature vectors. We use Sentibank [1] to extract 1200-dimensional feature vectors from images. From the social network we can get the adjacency matrix of users.

Comparison methods. To evaluate the performance of our model, we compare it with several baseline methods. All models are built using pytorch. The comparison methods are listed as follows:

Deep Neural Network (DNN): We get predictions of the encoded content features through a fully-connected neural network.

Long-Short Term Memory (LSTM): It does not consider emotion influence from friends and only takes the encoded content features as the input of LSTM.

Graph Convolutional Network (GCN): It is described in [8] and does not have LSTM. It takes the output of GCN as the input of the classifier.

Graph Convolutional Recurrent Network (GCRN): To analyze the the contribution of the attention mechanism, we train the GCRN model with mean aggregator described in [8], in which all the node features in the neighborhood have the same weight.

In our model, the auto-encoder is trained in advance. In the graph convolutional network, the neighbor size K=2 and the length of the timestep is 3.5 days. The hidden layer of LSTM contains 100 neurons and is activated by relu. The dropout rate is 0.5. Cross-entropy loss is used in training.

Metrics. We use F1-measure to verify the performance of each algorithm.

$$F1 = \frac{2 * precision * recall}{precision + recall} \tag{12}$$

Specifically, we use both macro-F1 and micro-F1 to evaluate the performance of different models. Macro-F1 is considered as the average F1 value of different classes. When calculating micro-F1, we first get the sum of the TP (true positive), FP (false positive) and FN (false negative) value of each class, and then calculate the micro-precision and micro-recall to get the micro-F1 using Equation 12.

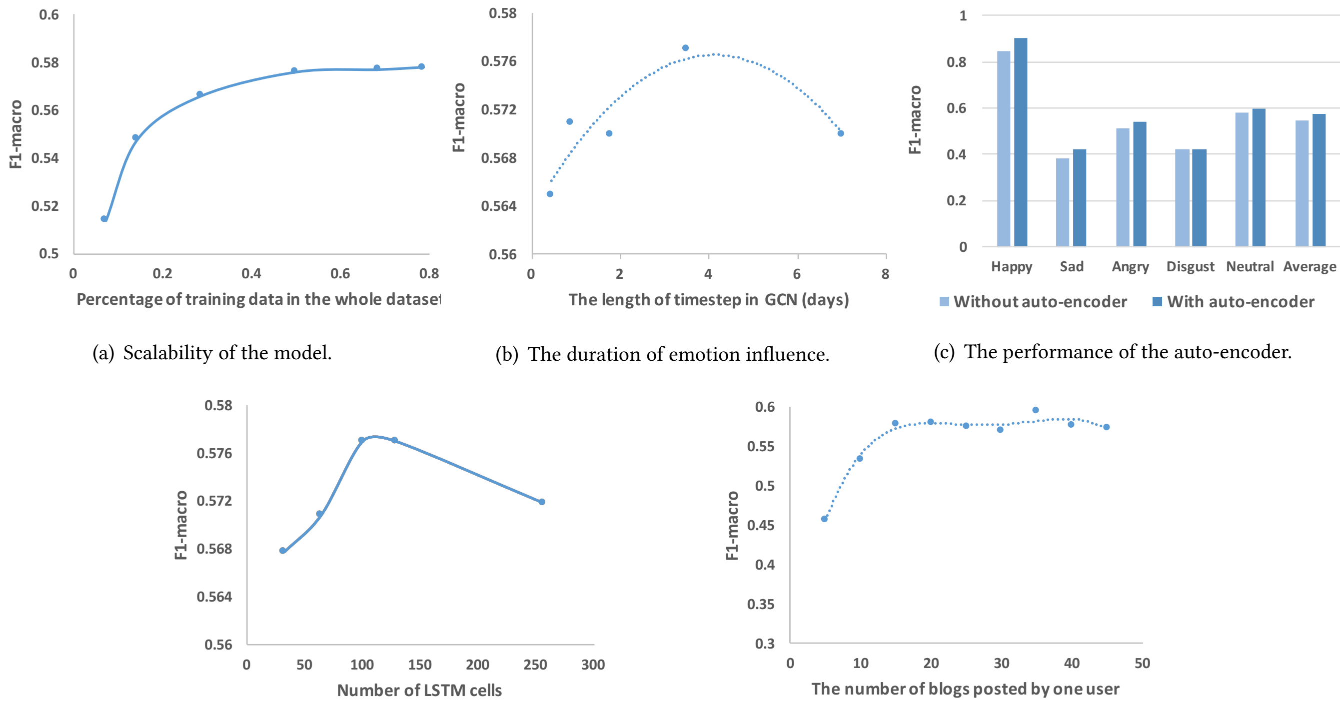
Experimental results

Performance analysis. The F1-measure of our model and the comparison methods are shown in Table 1. All methods have higher micro F1 values because happiness accounts for a greater proportion of all emotions and has higher accuracy. And they all perform better when distinguishing between positive and negative emotions. The experimental results confirm the effectiveness of our model. On this basis, we further analyze the following aspects:

1) Compared with the GCN model, the GCRN model gets an improvement of 4.2%-4.9% on macro-F1, which validates the importance of incorporating users' previous emotion states and preferences into emotion analysis.

2) Compared with basic LSTM, the GCRN models get improvements of 3.4%-4.6% on macro-F1, which proves the effectiveness of considering emotion influence by aggregating the features from social network friends.

3) When using the attention mechanism, the model gets an improvement of 1.2% on macro-F1. The results prove that focusing on friends who have greater impact on the user's



(a) Scalability of the model.

(b) The duration of emotion influence.

(c) The performance of the auto-encoder.

(d) Relations between macro-F1 and LSTM cells.

(e) Relations between macro-F1 and the number of blogs posted by one user.

Figure 6: Parameter sensitivity analysis.

emotion can benefit user emotion analysis. We also notice that the model gets greater improvements (1.4%-1.8% in terms of F1-measure) in both positive and negative emotions than neutral ones. This indicates that when using attention mechanism the model can focus on friends with similar emotion states.

Scalability. To evaluate the scalability of our method, we conduct experiments on different scales of dataset and the result is shown in Figure 6(a). At first, the performance increases with the scale of dataset, then it tends to be stable when training percentage is larger than 50%. The results verify the scalability of the proposed method.

Structure analysis. To explore the performance of our auto-encoder model, we compare it with a basic LSTM model without auto-encoder and an LSTM model with single-layer auto-encoder. The single-layer model only contains one hidden layer to represent the joint feature. Figure 6(c) shows the average F1-measure of these models. Compared with the single-layer auto-encoder model, our model avoids the imbalance in the training process due to the difference in feature length, which improves the performance.

Parameter sensitivity analysis. We conduct experiments on different length of time in GCN to analyze the duration of emotion influence. Figure 6(b) shows the average F1-measure of different Δt in Equation 6. If the time period is too short, we can not get enough tweets to guide the prediction. But if it is too long, the tweets may not have enough influence on the user. We can see that the model with a 3-day length achieves better performance.

Table 2: The F1-measure of different sizes of neighborhood

	Happy	Sad	Angry	Dis -gust	Neu -tral	F1 -macro
K = 1	0.892	0.421	0.521	0.382	0.595	0.562
K = 2	**0.902**	0.421	**0.540**	**0.422**	0.600	**0.577**
K = 3	0.896	**0.424**	0.535	0.392	**0.606**	0.570

Table 2 shows the results considering different sizes of the local neighborhood (up to depth K). Although most emotion influence comes from direct links of the users, friends who are not directly linked to the users still have some influence on them.

Figure 6(d) shows the average F1-measure of different number of LSTM neurons. Our model reached the highest performance when LSTM has 100 memory cells. The performance decreased when the number of cells increased.

Therefore, we set the number of LSTM memory cells in the experiments as 100.

Figure 6(e) shows the relationship between the number of tweets posted by one user and the average classification performance. When the number of tweets is less than 15, the classification performance increases as the number increases. Then it maintains basically stable. This shows that the user's personalized information can be learned after enough amount of data.

7 CONCLUSION

In this paper, we propose an attention-based graph convolutional recurrent network to analyze users' emotion status. We combine emotion influence with user's personalized content features. The experimental results prove the effectiveness of our method. We further discuss the length of time that emotion influence can last and the size of neighborhood to which it can spread. Our approach can be applied to many areas, including public opinion monitoring and product promotion in social networks.

In the future, we can adopt more social network information into emotion modeling, such as the interaction between users.

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