

MULTIMODAL HYPERGRAPH LEARNING FOR MICROBLOG SENTIMENT PREDICTION

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ABSTRACT

Microblog sentiment analysis has attracted extensive research attention in the recent literature. However, most existing works mainly focus on the textual modality, while ignore the contribution of visual information that contributes ever increasing proportion in expressing user emotions. In this paper, we propose to employ a hypergraph structure to formulate textual, visual and emoticon information jointly for sentiment prediction. The constructed hypergraph captures the similarities of tweets on different modalities where each vertex represents a tweet and the hyperedge is formed by the “centroid” vertex and its k -nearest neighbors on each modality. Then, the transductive inference is conducted to learn the relevance score among tweets for sentiment prediction. In this way, both intra- and inter- modality dependencies are taken into consideration in sentiment prediction. Experiments conducted on over 6,000 microblog tweets demonstrate the superiority of our method by 86.77% accuracy and 7% improvement compared to the state-of-the-art methods.

Index Terms— Sentiment analysis, Microblog, Hypergraph learning, Multi-modality

1. INTRODUCTION

Nowadays have witnessed the proliferation of microblogs like Twitter and Sina Weibo, with ever increasing amounts of multimedia data accumulated daily. Taking Sina Weibo for instance, it hits a 143 million mark of monthly active users by March 2014, growing by 10.9% compared to Dec 2013. Microblog has served as one of the most popular platforms for social network users to express their feelings over their topics of interests. It has therefore attracted extensive research interest on sentiment mining [1], which involves several emerging applications such as event monitoring, social network analytics, and commercial recommendations, etc.

One significant trend of microblog lies on the increasing amount of multi-modality information, such as image, video, short text, together with rich emoticons. One explanation is that more and more social network users use different devices in tweeting, under which circumstances it is more convenient to upload photos and emoticons instead of typing plain texts.

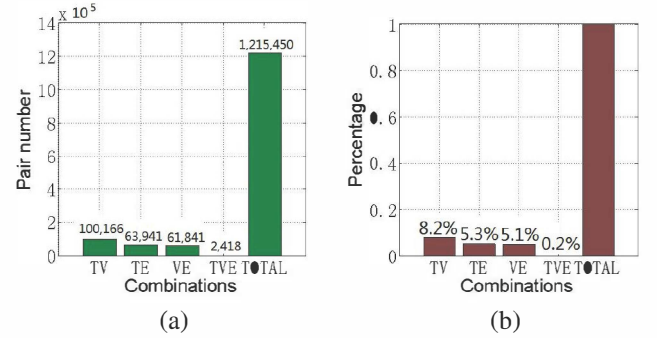


Fig. 1. Number (a) and percentage (b) of tweet-tweet pair based on similarity of different modality combinations, where TV, TE, VE, TVE and TOTAL stand for Textual-Visual modality, Textual-Emoticon modality, Visual-Emoticon modality, Textual-Visual-Emoticon modality, and total pair number, respectively.

However, for sentiment analysis, most current research still retains on analyzing the solely text channel, without regard to the rich multi-modality information [1], [2], [3], [4], [5].

On the contrary, it has not been well investigated. It has been revealed in the cognitive science [6] that the modalities are highly distinguished from each other for sentiment analysis, upon which multi-modality analysis is highly encouraged. Let us take Sina Weibo for a quantitative instance. We take over 5,000 tweets to count the number of tweet-tweet pairs based on similarity over the different modality combination. As shown in Fig.1, we take each tweet and its k -nearest (here $k = 220$) neighbors as the statistical objects on the three modalities according to their similarity. For example, the pair number on Textual-Visual modality means the number of tweet-tweet pairs that both tweets are similar on textual and visual modalities, indicating roughly the dependency between both modalities. The conclusion here is that visual and textual modalities are indeed highly independent. Subsequently, it is imprecise to simply fuse similarities over different modalities to reveal the tweet similarity as well as the emotional correlation.

In this paper, we propose a multimodal hypergraph (termed MHG) method for cross-modality (a.k.a., textual, visual, and emoticon) microblog sentiment prediction. MHG

first computes the pairwise tweet similarities on different modalities respectively, and then a multimodal hypergraph model is constructed, where each vertex represents a tweet and the hyperedges are formed by the “centroid” vertex and its k -nearest neighbors on different modalities. Alternating optimization [7] is leveraged to learn the final relevance score of each tweet for microblog sentiment prediction. Quantitative comparisons show that our method outperforms alternative approaches with 86.77% accuracy and 7% improvement for multi-modality learning.

The rest of paper is organized as follows. Related work is discussed in Section 2. The proposed method is provided in Section 3. Experimental results are provided in Section 4. In Section 5, we conclude the paper.

2. RELATED WORK

2.1. Sentiment Prediction

For sentiment analysis, most existing works mainly focus on textual content, which could be divided into two categories, i.e., dictionary-based approaches and learning-based approaches. Dictionary-based approaches rely on the pre-defined sentiment dictionaries, which employ text statistics, such as point mutual information (PMI) and TF-IDF, for sentiment classification. One recent work in [5] predicted the sentiment of reviews by the average semantic orientation of the phrases in the review. However, such approach is restricted by the difficulty of obtaining satisfied sentiment dictionaries. On the other hand, current works on text mainly focus on learning-based approach. For example, the method in [4] applied Naive Bayes, MaxEnt and SVM to deploy learning schemes for sentiment prediction of chapter-level documents.

Visual sentiment prediction has recently been studied in our recent work [8], we have demonstrated that mid-level visual attributes, named Adjective Noun Pairs (ANP), performed better than low-level attributes in visual sentiment analysis. And a so-called SentiBank detector library has been released for the purpose of predicting sentiment scores for images or videos.

Recently, multimodal sentiment analysis has attracted ever increasing research attentions. Perez [9] and Wang [10] proposed to learn SVM and Logistic Regression respectively over features concatenated from all modalities. However, a common defect of these works is neglecting the independence of each modality. To model the modality independence, Chen [11] proposed a SVM voting method for web page classification by determining the categorization on output of two SVM models utilizing the semantic feature and the text feature, respectively. However, these two methods ignore the relevance among tweets as well as the similarity for overall semantic dependency.

2.2. Hypergraph Learning

A hypergraph is a graph which can connect three or more vertices with an hyperedge. The hyperedges can be constructed in different ways, such as feature-based hyperedges that connect the vertices with a certain feature [7], [12], and distance-based hyperedges formed by the “centroid” vertex and its k -nearest neighbors [13], [14], which are effective to estimate the overall semantic dependency among vertices. In addition to reflecting the higher order information, the hypergraph-based method could be used to take advantage of abundant unlabeled dataset. Due to the advantages of hypergraph on high-order data modelling, it has been widely applied in various tasks, such as classification [14], ranking [13], [7], and segmentation [15].

3. MHG-BASED SENTIMENT PREDICTION

3.1. The Problem

Each microblog can be regarded as consisting of three modalities, i.e., textual, visual, and emoticon. The bag-of-words features are extracted from the three modalities, respectively, i.e., the bag-of-textual-words $F_i^{botw} = \{w_1^t, \dots, w_k^t, \dots, w_{m_t}^t\}$, the bag-of-visual-words $F_i^{bovw} = \{w_1^v, \dots, w_k^v, \dots, w_{m_v}^v\}$, which are extracted by using 1,200 dimensional SentiBank feature [8], and the bag-of-emoticon-words $F_i^{boew} = \{w_1^e, \dots, w_k^e, \dots, w_{m_e}^e\}$. Taking the textual modality as an example, we let F_i^{botw} denote the bag-of-textual-words of the i -th tweet x_i , in which w_k^t represents the frequency of the k -th textual sentiment word in the i -th tweet. The F_i^{bovw} and the F_i^{boew} can be described in a similar way. Then, the tweet x_i can be represented by $x_i = \{F_i^{botw}, F_i^{bovw}, F_i^{boew}\}$. The target is to predict the sentiment of a given tweet by jointly investigating F_i^{botw} , F_i^{bovw} and F_i^{boew} .

3.2. The Method

The proposed framework is illustrated in Fig.2. In feature extraction, the features are extracted from the three modalities, textual, visual and emoticon modality, respectively ¹.

To construct the hypergraph, the Euclidean distance between each two tweets is calculated for each modality respectively. According to the similarity, the constructed hypergraph structure is consisted of the vertex set and the hyperedge set. An example is shown in Fig. 2. There are 7 vertices $\{v_1, \dots, v_7\}$ and 6 hyperedges $\{e_1, \dots, e_6\}$ in the hypergraph, where each vertex represents a tweet and each hyperedge is formed by the ‘centroid’ vertex and its k -nearest neighbors on each modality. Two ‘centroid’ vertices, v_3 and v_6 , are shown together with their 2-nearest neighbors,

¹More details about data preprocessing in feature extraction will be given in the experiment section

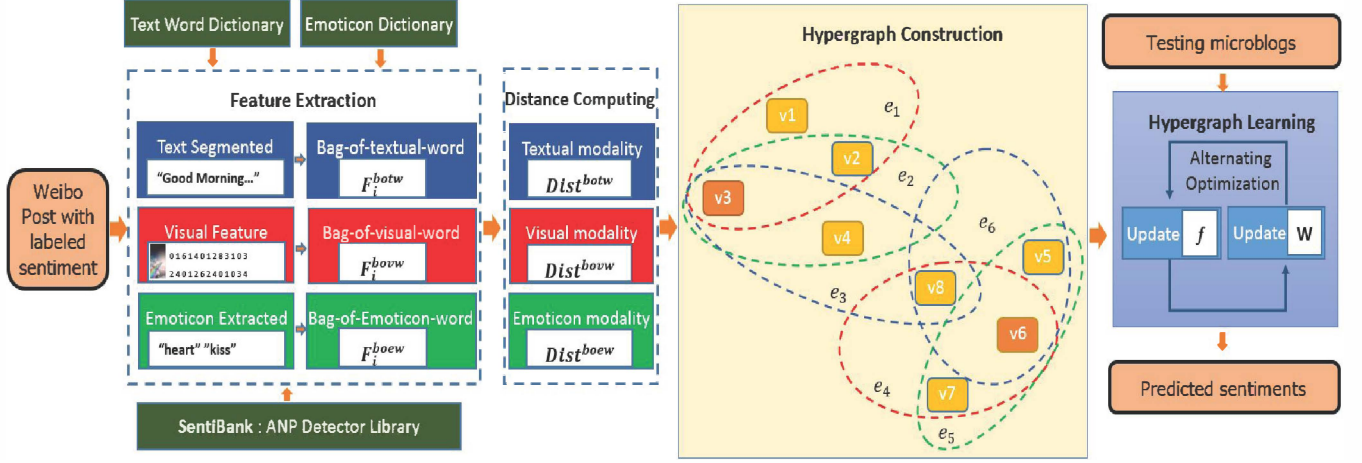


Fig. 2. Schematic illustration of the MHG-based sentiment prediction

where different colors of hyperedges mean different modalities. Note that there should be 21 hyperedges since each vertex could be a ‘centroid’ vertex. For simplification and clearness, we just take v_3 and v_6 as the ‘centroid’ vertices in the illustration. The constructed hypergraph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, w)$ consists of the vertex set \mathcal{V} , the hyperedge set \mathcal{E} , and the hyperedges weights w . The weight of each hyperedge is represented by $w(e)$. The structure of the probabilistic hypergraph is represented by a $|\mathcal{V}| \times |\mathcal{E}|$ incidence matrix \mathbf{H} :

$$\mathbf{H}(v_i, e_j) = \begin{cases} s(j, i) & \text{if } v_i \in e_j \\ 0 & \text{otherwise} \end{cases}, \quad (1)$$

where $s(j, i)$ is the relevance between v_i and e_j . $s(j, i)$ is calculated by:

$$s(j, i) = \exp\left(-\frac{\text{dist}(i, j)^2}{(\sigma \hat{d})^2}\right), \quad (2)$$

where $\text{dist}(i, j)$ is distance between v_i and the centroid vertex of e_j , \hat{d} is the mean pairwise distance for the corresponding modality, and the parameter σ is empirically set to the median value of the distance of all view pairs. The weight of each hyperedge is initialized as 1.

For a vertex $v \in \mathcal{V}$, its vertex degree is calculated by:

$$d(v) = \sum_{e \in \mathcal{E}} w(e)h(v, e). \quad (3)$$

For a hyperedge $e \in \mathcal{E}$, its vertex degree is calculated by:

$$\delta(e) = \sum_{v \in \mathcal{V}} h(v, e). \quad (4)$$

We further denote \mathbf{D}_v , \mathbf{D}_e and \mathbf{W} as the diagonal matrices of the vertex degrees, the hyperedge degrees and the hyperedge weights in $\mathcal{G} = (\mathcal{V}, \mathcal{E}, w)$, respectively.

In hypergraph learning, we employ the hypergraph-based transductive inference method introduced in [7] to estimate the relevant scores of tweets for different sentiments by iteratively updating the relevance score vector f and the hyperedge weights \mathbf{W} .

The task in the learning process can be summarized to minimize the following loss function:

$$\begin{aligned} \arg \min_{f, \mathbf{W}} \{ & \Omega(f) + \lambda R_{emp}(f) + \mu \sum_{i=1}^{n_e} w_i^2 \}, \\ \text{s.t. } & d(v) = \sum_{e \in \mathcal{E}} w(e)h(v, e) \end{aligned} \quad (5)$$

where f is the relevance score vector to be learned, $\Omega(f)$ is a regularizer based on Normalized Laplacian [12] on hypergraph, $R_{emp}(f) = \|f - y\|^2$ is empirical loss, and $\sum_{i=1}^{n_e} w_i^2$ is the l-2 regularizer on the hyperedge weights. $\Omega(f)$ can be defined as:

$$\begin{aligned} \Omega(f) = & \frac{1}{2} \sum_{e \in \mathcal{E}} \sum_{u, v \in \mathcal{V}} \frac{w(e)h(u, e)h(v, e)}{\delta(e)} \\ & \times \left(\frac{f(u)}{\sqrt{d(u)}} - \frac{f(v)}{\sqrt{d(v)}} \right)^2 \end{aligned} \quad (6)$$

Let $\Theta = \mathbf{D}_v^{-\frac{1}{2}} \mathbf{H} \mathbf{W} \mathbf{D}_e^{-1} \mathbf{H}^T \mathbf{D}_v^{-\frac{1}{2}}$, and $\Delta = \mathbf{I} - \Theta$ be hypergraph Laplacian. The normalized cost function can be written as follow:

$$\Omega(f) = f^T \Delta f \quad (7)$$

There are two variables \mathbf{W} and f to be optimized, which denote the diagonal matrices of hyperedge weights and relevance score vector respectively. Both variables are learned by using an alternating optimization [7]. That is, we fix one and optimize the other one in each iteration:

Algorithm 1 MHG-based Sentiment Prediction

Input : The microblog tweets $X = \{x_1, x_2, \dots, x_n\}$ whose sentiment needs to be predicted.

Output : The relevance score vector f for microblog tweets sentiment prediction.

Step 1. Hypergraph Construction

1. Extract the textual features, the visual features and the emoticon features of each tweet x_i .
2. Construct hyperedge based on the pair-wise tweet distances.
3. Generate the incidence matrix \mathbf{H} , diagonal matrices of the vertex degrees \mathbf{D}_v and diagonal matrices of hyper-edge degrees \mathbf{D}_e respectively.

Step 2. Learning on Hypergraph

1. Update f by Eq. (8).
 2. Update \mathbf{W} by Eq. (9).
 3. Repeat 1 and 2 until convergence.
 4. Get the sentiment prediction result of microblog tweet based on f .
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$$\arg \min_f \Phi(f) = \arg \min_f \{f^T \Delta f + \lambda \|f - y\|^2\} \quad (8)$$

$$\begin{aligned} \arg \min_w \Phi(f) &= \arg \min_f \{f^T \Delta f + \mu \sum_{i=1}^{n_e} w_i^2\} \\ \text{s.t. } d(v) &= \sum_{e \in \mathcal{E}} w(e) h(v, e) \end{aligned} \quad (9)$$

We summarize the overall procedure for both model learning and sentiment prediction algorithm in Algorithm 1.

4. EXPERIMENTS

In our experiments, the objectives are two-fold: (1) whether using multi-modality can improve the accuracy of sentiment prediction, and (2) whether using hypergraph is a better choice in modeling multi-modality data. In the following, we will report our implementation details on experiment setting, preprocessing, and quantitative results.

4.1. Experimental Settings

The dataset is acquired from the platform of Sina Weibo containing 6,000 tweets with textual, visual and emoticon content simultaneously. The dataset is selected using the top ten hot topics from Sina Weibo topic list from Feb 2014 to Apr 2014, which involves various topics such as trivial affairs, weather, work, stars, films, international events.

The problem of sentiment prediction is set in two manners, i.e., two-way (positive and negative) classification and three-way classification (positive, negative and neutral).

Table 1. Performance comparison of the proposed method with textual-based methods.

| Methods | Two-Class | Three-Class |
|---------|-----------|-------------|
| NB | 59.18% | 43.33% |
| LR | 65.76% | 45.82% |
| SVM | 65.95% | 49.94% |
| HG_text | 60.31% | 43.80% |
| MHG | 86.77% | 66.68% |

4.2. Baselines

To demonstrate the superiority of multi-modality approach compared to single modality method, the proposed method is compared to Cross-media Bag-of-words Model (CBM) based methods including Naive Bayes, Logistic Regression, and SVM, where CBM-Logistic Regression is the current state-of-the-art method in cross-media microblog sentiment prediction [10]. We also compare the proposed method to a hypergraph learning method using only the textual feature only. In the following experiment, without loss of generality, these compared methods are denoted by as “NB”, “LR”, “CBM-NB”, “CBM-LR”, and “HG_text”, respectively.

To justify the independence of each modality on multi-modality model, we compared our method with the following methods: 1) Combined Hypergraph-based method [13]. In this method, a total similarity are estimated on all modalities in simple way, which means, in our experiment, the three bag-of-words models on three modalities are combined to compute a total similarity for two tweets. The method is denoted as “HG_combine” in our experiment.

2) SVM voting method [11]. In this method, the authors use one SVM classifier for one modality and vote to product the result by combining the results of three modalities.

3) Multi-kernel SVM. In this method, each modality is provided with a kernel(‘RBF’ kernel) in the SVM classifier.

4) MHG method. In our method, we construct the hypergraph based on different vertex-vertex similarities on different modalities, which take the independence of each modality into consideration.

All the classification experiments are performed with 10 fold cross-validation. Classification accuracy is employed as the evaluation.

4.3. Preprocessing

To generate the bag-of-textual-words, each text is segmented before feature extraction by using Chinese auto-segmentation system ICTCLAS [16], which is different from English text processing. Meanwhile, the textual word dictionary contains 2,547 words, which are selected by the frequency in text corpus from the sentiment word dictionary incorporation of HowNet and NTUSD. After textual segmentation, the textual word dictionary is used to extract the textual features.

Table 2. Performance comparison of different methods using multi-modal data.

| Methods | Two-Class | Three-Class |
|---------|-----------|-------------|
| CBM-NB | 63.67% | 45.17% |
| CBM-LR | 79.88% | 59.49% |
| CBM-SVM | 81.61% | 62.88% |
| MHG | 86.77% | 66.68% |

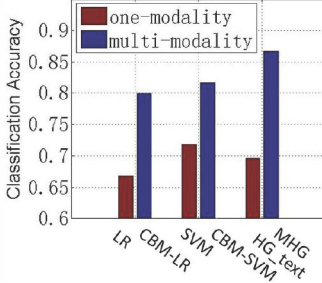


Fig. 3. Two-way sentiment classification with different approaches

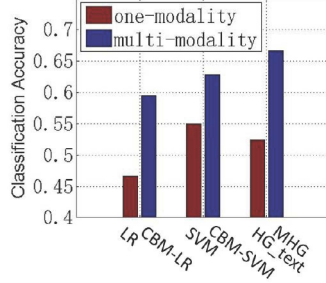


Fig. 4. Three-way sentiment classification with different approaches

To generate the bag-of-visual-words, we use SentiBank, a kind of ANP detector library [8], to transform the low-level features of image into mid-level features (1200 ANPs). Then, the confidence coefficients of ANPs higher than 0.8 are employed.

To generate the bag-of-emoticon-words, we construct the emoticon dictionary with the emoticons used high frequently in text corpus. There are finally 49 emoticons manually selected to ensure obvious emotion in final emoticon dictionary. After that, we just use the emoticon dictionary to extract the emoticon features and construct the bag-of-emoticon-words.

4.4. Results and Discussion

Table 1 shows the performance comparison of the proposed method with textual-based by using Naive Bayes, Logistic Regression, SVM and our method. Table 2 shows the performance comparison of different methods using multi-modalities. As shown in these results, we can observe that the proposed method can achieve better performance than textual-based methods. More specifically, MGH outperforms HG_text with textual information individually by 26% for the two-way classification. In comparison with other multi-modal methods, the proposed method achieves better performance on microblog sentiment prediction.

Fig.3 and Fig.4 show the comparisons of one-modality model (average result of three modalities) and multi-modality model by employing different approaches, on two-way and three-way sentiment classifications, respectively. These results demonstrate that the using of multi-modalities can outperform the method of using single modality apparently.

Table 3 shows the performance comparison on modality independence by using HG_combine, SVM voting, Multi-

Table 3. Accuracy of Comparison Experiment on Modality Independence

| HG.combine | SVM voting | Multi-kernel SVM | MHG |
|------------|------------|------------------|--------|
| 63.81% | 80.79% | 85.96% | 86.77% |

Table 4. The Examples of Microblog Tweet with Sentiment Predicted by Using HG_combine and MHG Respectively

| Text(Translated) | Image | Emoticon | Results |
|--|-------|----------|------------------------------------|
| Well, I hope Meizu (mobile phone) will become street shooting weapon: matching visual glasses as a viewfinder, wire as the shutter line. In this way, there is no pressure on street shooting. | | | gt: 1 HG_combine: -1 MHG: 1 |
| It (mobile phone operating system) is too unstable, and recovers like ventilation. | | | gt: -1 HG_combine: 1 MHG: -1 |
| Although here comes a little girl, my sister must be the one most loving me except my parents. Although I love the new girl, I love my sister more, and forever. | | | gt: 1 HG_combine: 1 MHG: 1 |
| After courtship for 7 years, you finally enter the wedding hall. You must be always happy, and full of blessings for your happiness. Be quick to become new dad and mom. | | | gt: 1 HG_combine: 1 MHG: 1 |
| After watching Hot Mom Story, I have insomnia unexpectedly with blank mind. I can't sleep all the time. Will the dark circle under eyes be darker? I decide to heighten the pillow to have a try. | | | gt: -1 HG_combine: 1 MHG: 1 |
| Qingyun never fails me. He really can't play bad movies. The scene of the fire disaster film is pretty shocking, and its plot is very compact. It's so intense that someone's arm was scratch and appeared bruises. It's absolutely the dish of disaster film fans. Small heart can't take it. Dear, go, go, go. | | | gt: 1 HG_combine: -1 MHG: -1 |

kernel SVM, and MHG on two-way classification. As shown in the results, the methods considering modality independence (SVM voting method, Multi-kernel SVM, and MHG) outperforms HG_combine. In addition, due to the relevance among tweets and the similarity for overall semantic dependency, MHG achieves better performance than SVM voting method and Multi-kernel SVM.

Table 4 shows examples of microblog tweets with sentiment predicted by using HG_combine and MHG, respectively. Here, ground truth (gt) is the manually annotated category of the tweet (-1 is negative and 1 is positive). $f^{HG_combine}$ and f^{MHG} are the final relevance scores for corresponding tweet by employing HG_combine and MHG, respectively. The relevance score $f^{HG_combine} \in [-2.13e^{-2}, 4.58e^{-4}]$ and $f^{MHG} \in [-2.15e^{-2}, 2.37e^{-2}]$, where negative values and positive values indicate that the tweets belong to negative category and positive category respectively. According to the rele-

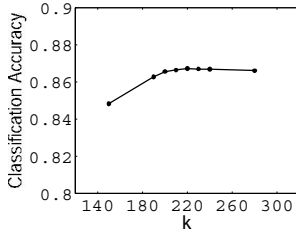


Fig. 5. Two-way sentiment classification with different k values for number of nearest neighbors

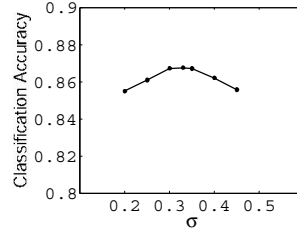


Fig. 6. Two-way sentiment classification with different coefficient σ of the tweet pairwise distance

vance scores, the sentiment prediction results can be achieved.

Fig. 5 and Fig. 6 show the impact of the parameters k and σ in the two-way sentiment classification experiments of the MHG method respectively. As shown in the results, we can notice that the performance is stable when the parameters vary in a large range. This can demonstrate that the proposed method is robust to the parameter settings.

5. CONCLUSIONS

In this paper, we employ multimodal hypergraph-based method to predict microblog sentiment. Different from existing methods using textual information only, our method simultaneously employ textual, visual and emoticon information in the prediction process. In our method, a hypergraph structure is constructed using multimodal information and transductive learning is conducted to estimate the relevance each tweet to the sentiment categories. Experiments are conducted on over 6,000 microblog tweets and the results demonstrate the effectiveness and superiority of our method by 86.77% accuracy and 7% improvement compared to state-of-the-art method.

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