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Hidden Topic-Emotion Transition Model for Multi-Level Social Emotion Detection

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Abstract

With the fast development of online social platforms, social emotion detection, focusing on predicting readers' emotions evoked by news articles, has been intensively investigated. Considering emotions as latent variables, various probabilistic graphical models have been proposed for emotion detection. However, the bag-of-words assumption prohibits those models from capturing the inter-relations between sentences in a document. Moreover, existing models can only detect emotions at either the document-level or the sentence-level. In this paper, we propose an effective Bayesian model, called hidden Topic-Emotion Transition model, by assuming that words in the same sentence share the same emotion and topic and modelling the emotions and topics in successive sentences as a Markov chain. By doing so, not only the document-level emotion but also the sentence-level emotion can be detected simultaneously. Experimental results on the two public corpora show that the proposed model outperforms state-of-the-art approaches on both document-level and sentence-level emotion detection.

Keywords: Social Emotion Detection, Sentiment Analysis, Topic Model, Hidden Topic-Emotion Transition Model

1. Introduction

With the fast development of social web, more and more users tend to share their opinions about social events, post discussions of political movements and express their preferences over products and services on online platforms [1, 2]. Some news portals, for example, the Sina news, allows readers to vote for their emotions after reading a news article. Essentially, each news article could be

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associated with multiple emotions of its readers over a predefined set of emotion categories. An example of a news article with the readers' emotion votes is shown in Figure 1. Here, the readers' emotion votes form the document-level emotion labels which are observed. We assume that such document-level emotion labels can be inferred from the unobserved sentence-level topics and emotions. In Figure 1, we manually annotate the sentence-level topics and emotions and display them against a shaded background to denote that they are unobserved.

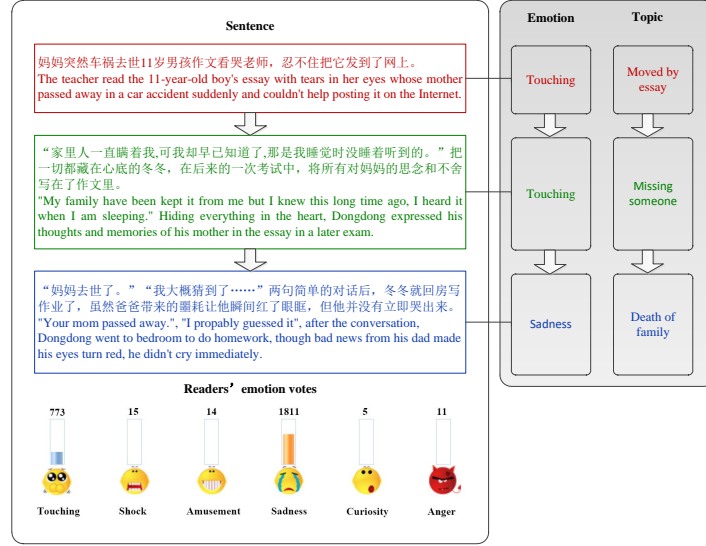


Figure 1: Excerpt of a news article from Sina and its corresponding reader votes over predefined emotion classes. Sentence-level topics and emotions in the left shaded pane are manually annotated and unobserved.

Approaches for social emotion detection can be categorized into two types: discriminative-model based and topic-model based. By casting emotion detection into a classification problem, many discriminative-model based methods have been proposed [3, 4, 5], such as the logistic regression model with emotion dependency [6] and the social opinion mining model based on K-Nearest Neighbour (KNN) [7]. However, such approaches are unable to reveal the latent topic information in order to understand how the emotions are evoked. To address this problem, topic-model based approaches have been largely applied for social emotion detection [8, 9]. Generally, the hidden topics and emotions are mined simultaneously from the documents by adding an emotion layer into topic models such as Latent Dirichlet Allocation (LDA) [10]. However, most of them make the “bag-of-words” assumption, i.e., the order of words is ignored and the topic or emotion assignment of each word in the document is independent from each other. The simplified assumption ignores the structural information in a document, which might be critical for social emotion detection. A news article contains a title typically summarizing an event, followed by several structured

and coherent groups of sentences describing the detailed information of the event. As can be seen in Figure 1 that (1) one sentence typically only describes a single event/topic; (2) the event or topic directly triggers reader’s emotions; (3) successive sentences tend to share the same emotion or topic.

Based on the above observations, we propose a novel probabilistic graphical model, called hidden Topic-Emotion Transition (TET) model to model the emotion and topic transitions simultaneously. In specific, TET considers each sentence as a basic unit and all the words in the same sentence are assumed to share the same topic label and the same emotion label. The topic transition and emotion transition in successive sentences are modelled via a hidden Markov model and learned from data, in a way avoiding the document-level bag-of-words assumption. By doing that, TET can detect both the document-level and the sentence-level emotions though it only requires data with the document-level emotion labels for training. We conduct experiments on the two public corpora, a news dataset and a blog dataset. Experimental results show that TET outperforms several state-of-the-art approaches for both document-level and sentence-level emotion detection and also detects underlying topics which evoke the corresponding emotions.

2. Related Work

Our work is related to two lines of research: social emotion detection and topic models for emotion/sentiment analysis [11].

2.1. Social Emotion Detection

Approaches for social emotion detection can be mainly divided into two categories: discriminative-model based and topic-model based.

For the first category, social emotion detection is often casted as a classification problem. If only choosing the strongest emotion as the label for a given text, emotion detection is essentially a single-label classification problem. Lin et al. [12] studied the classification of news articles into different categories based on readers’ emotions with various combinations of feature sets. Strapparava and Mihalcea [13] proposed several knowledge-based and corpus-based methods for emotion classification. Quan et al. [6] proposed a logistic regression model with emotion dependency for emotion detection. Latent variables were introduced to model the latent structure of input text. Li et al. [14] combined biterm topic model and conventional neural network to detect single social emotion from short texts. Li et al. [15] incorporated domain-specific and universal knowledge into a unified sentiment classification framework to build a domain-adaptive sentiment classification model. Label propagation was employed to unify universal and domain-specific sentiment lexicons.

To predict multiple emotions simultaneously, emotion detection can be solved using multi-label classification. Bhowmick [16] presented a method for classifying news sentences into multiple emotion categories using an ensemble based multi-label classification technique. Wang et al. [17] output multiple emotions

with intensities using non-negative matrix factorization with several novel constraints such as topic correlation and emotion bindings. To predict multiple emotions with different intensities in a single sentence, Zhou et al. [18] proposed a novel approach based on emotion distribution learning. In the same vein, a relevant label ranking framework for emotion detection is proposed for predict multiple relevant emotions as well as the ranking of emotional intensity [19, 20]. A KNN-like approach called social opinion mining model (SOMM) was proposed in [7] where word embeddings were used to calculate word mover’s distance of all the documents via solving an optimizing problem. The average emotion distribution of the k nearest neighbors of a test document was then used for emotion prediction.

As for aspect-level sentiment classification, it can be seen as a fine-grained task in emotion detection. Wang et al.[21] employed an attention-based long short-term memory network for aspect-level sentiment classification. It can concentrate on different parts of a sentence when different aspects are considered as input. As word embedding has been proven to be a useful model for sentiment analysis and emotion detection, Li et al. [22] incorporated prior sentiment information into the embedding process to investigate the influence each word has on the sentiment label of both target word and context words. It can learn better representations for sentiment analysis.

However, discriminative-model based approaches are unable to detect and incorporate latent topic information to understand how the emotions are evoked. To address this problem, topic-model based approaches have been largely applied for social emotion detection [8, 9]. For example, the Emotion-Topic Model (ETM) [23] or the Sentiment Latent Topic Model (SLTM) [8] are similar to the Joint Sentiment-Topic (JST) model [24] in which an additional emotion or sentiment layer is inserted between the topic layer and the observed words in LDA so as to detect emotion- or polarity-bearing topics. Contextual Sentiment Topic Model (CSTM) [9] assumes each word is either drawn from a background theme, a contextual theme or a topic. Emotion classification is based on context-independent topics.

Our proposed approach belongs to the second category. However, while most existing topic model approaches are based on the bag-of-words assumption, our TET model takes the sentence sequential information into consideration and models the topic/emotion transitions explicitly which is crucial for social emotion detection.

2.2. Topic Models for Emotion/Sentiment Analysis

Emotion detection, classifying text into one or more emotion categories such as ‘Happy’, ‘Sad’ and ‘Surprise’, is closely related to sentiment analysis which typically classifying text into one of the three polarity categories, ‘Positive’, ‘Negative’ or ‘Neutral’. As such, we review topic modeling approaches to emotion or sentiment detection here.

Many topic-model based approaches have been proposed for detecting both sentiments and topics [25]. For example, the topic sentiment mixture model [26] jointly modelled topics and sentiments, and sampled a word either from

the background model or topical themes where the latter are further categorized into three sub categories, i.e., neutral, positive and negative sentiment models. The Joint Sentiment-Topic (JST) [24] inserted an additional sentiment layer into LDA for polarity-bearing topic detection. Aspect and sentiment unification model (ASUM) [27] extended JST by enforcing words in a single sentence to share the same topic and sentiment label. Emotion-Topic Model (ETM) [23] first generated a set of latent topics from emotions, followed by generating affective terms from each topic. Contextual Sentiment Topic Model (CSTM) [9] distinguished context-independent topics from both a background theme, which characterizes non-discriminative information, and a contextual theme, which characterizes context-dependent information across different collections. Two models have been proposed in [8]. One is Multi-Label Supervised Topic Model (MSTM), which generated a set of topics from words firstly, followed by sampling emotions from each topic. The other is Sentiment Latent Topic Model (SLTM), which generated topics from social emotions directly.

However, these models make the bag-of-words assumption and ignore word ordering. To address this problem, some approaches have explicitly considered the order of words and the structure of sentences for topic generation. For example, [28] assumed that words are either generated from the syntactic classes which are drawn from the previous syntactic class or from topics that are drawn randomly. To model topic transition, Hidden Topic Markov Model (HTMM) [29] modelled the topics of words in a document as a Markov chain and assumed that topic transitions can only occur between sentences. In a similar vein, structural topic model [30] assumed that words in a sentence share the same topic. Hidden Topic Sentiment Model (HTSM) [31] extended HTMM and models the combination of aspect and sentiment label of sentences as a Markov chain. It assumed that words within a sentence share the same aspect label and sentiment label and constrained the transitions with the assumption that only one sentiment polarity can be associated with a specific aspect in a document.

Our proposed TET model is partly inspired by HTSM, but differs from HTSM in several aspects: (1) HTSM only considers binary sentiment polarities and models the sentiment transitions simply by a switch variable, while TET models multi-class emotion transitions and takes emotion correlations into consideration; (2) Different from the assumption of HTSM that one topic in a document can only be associated with one polarity, in TET, one topic can be associated with different emotions in a document since the same topic might evoke different emotions of different readers. (3) HTSM utilizes the predefined aspects and is trained on documents annotated with aspect labels, while no such information is available in our data.

3. Methodology

In this section, we propose the hidden Topic-Emotion Transition (TET) model. In specific, TET considers each sentence as a whole and assumes all the words in the same sentence share the same topic label and the same emotion label. It models the topic/emotion transition in successive sentences via a

hidden Markov model, essentially avoiding the bag-of-words assumption at the document-level.

3.1. Hidden Topic-Emotion Transition Model

Assuming that we have a set of documents denoted as $\mathcal{D} = \{d_1, d_2, \dots, d_{|D|}\}$, where each document d consists of m_d sentences denoted as $\mathcal{S} = \{s_1, s_2, \dots, s_{m_d}\}$, and each word in the sentences is an item from a vocabulary with V distinct terms denoted as $\{1, 2, \dots, V\}$. Let E be the number of distinct emotion labels, and an emotion label is denoted as $e \in \{1, 2, \dots, E\}$. Also, T is the total number of topics and a topic label is denoted as $t \in \{1, 2, \dots, T\}$. For a given document d , its document-specific topic-emotion proportion θ_d is assumed to be drawn from a shared Dirichlet distribution, i.e., $\theta_d \sim \text{Dir}(\alpha)$. Each sentence s_i in d has N_{s_i} words and is associated with an emotion label e_i and a topic label t_i , which is sequentially drawn from a document-specific Markov chain. As the topic and emotion labels of sentences are unobservable, we introduce a latent variable ψ to control the topic transition and τ to control the emotion transition. The plate diagram of TET is given in Figure 2. In what follows, we will describe how topic and emotion transitions are modelled before presenting the overall generative process for TET.

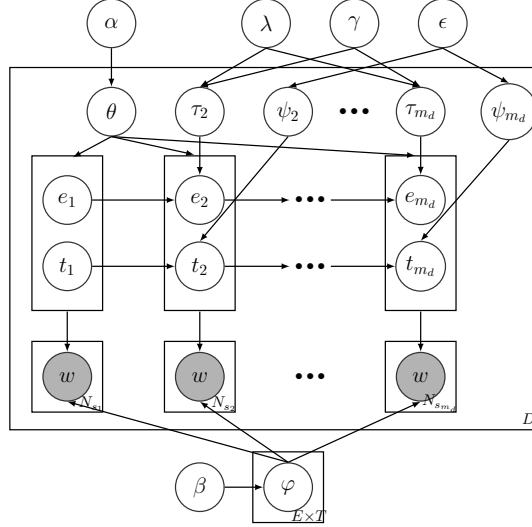


Figure 2: Graphical model for the proposed hidden Topic-Emotion Transition (TET) model.

3.1.1. Topic Transition

Since topics are inferred in a totally unsupervised manner without any prior knowledge, it is difficult to model the probabilities of topic transitions explicitly as a transition matrix. Therefore, we employ ψ_i as a switch variable to indicate whether there is a topic transition between s_{i-1} and s_i . As observed in Figure 1,

two successive sentences are less likely to share similar topics if their contents are very different. Therefore, it is reasonable to assume that the more similar two sentences are in terms of their content, the less likely there will be a topic transition between them. Several linguistic features in the adjacent sentences are employed to guide the topic transition. The probability of the switch variable ψ_i is defined as follows:

$$p(\psi_i | s_i, s_{i-1}, s_{i+1}, \epsilon) = \frac{1}{1 + \exp(-\epsilon^\top f_t(s_i, s_{i-1}, s_{i+1}))}, \quad (1)$$

where ϵ is the feature weights and $f_t(s_i, s_{i-1}, s_{i+1})$ is the topic transition feature function which takes the current sentence s_i , the previous sentence s_{i-1} and the next sentence s_{i+1} as input and outputs a feature vector. It includes: (1) content-based cosine similarity between s_i and s_{i-1} ; (2) sentence length ratio of s_i to s_{i-1} ; (3) the relative position of s_i in d ; (4) the content-based cosine similarity difference between (s_i, s_{i-1}) and (s_i, s_{i+1}) . The first three features are inspired by [31], while the last one assumes that there is no topic transition from the previous sentence to the current sentence if the current sentence is more similar to the previous sentence than the next one.

3.1.2. Emotion Transition

Assuming that an emotion lexicon consisting of words with their corresponding emotion distributions is available, i.e., each word is associated with multiple emotion labels with different intensities. We use $ES(w, e)$ to denote the emotion score of a word w associated with emotion e . We will show later in this section how to generate the emotion lexicon from the training data.

As some emotions co-occur more often than the others, we believe that such information would be useful for the derivation of emotion transitions. The Pearson coefficient between two emotions e_j and e_k , denoted as λ_{e_j, e_k} is calculated from the training set in the following way: First, each emotion e_j is represented as a vector EV_j with D dimensions where D is the number of documents in the training set and each element of the vector, $EV_j[i]$, is the number of votes for emotion e_j in the i th document. Then, the Pearson coefficients between two emotions e_j and e_k is calculated as:

$$\lambda_{e_j, e_k} = \frac{\text{cov}(EV_j, EV_k)}{\sigma_{EV_j} \sigma_{EV_k}}. \quad (2)$$

where $\text{cov}(\cdot)$ denotes the covariance and σ denotes standard derivation. The value of Pearson coefficient ranges from -1 to 1 , with a value of 1 indicating positive correlation and -1 indicating negative correlation. A value of 0 shows that the two emotions are independent from each other. We convert the Pearson coefficient values to the range of $[0, 1]$ using $\frac{\lambda_{e_j, e_k} + 1}{2}$ so that they can be used as the probabilities measuring how strongly two emotions e_j and e_k are related to each other.

After defining $ES(w, e)$ and λ_{e_j, e_k} , we can construct τ_i , the $E \times E$ emotion transition matrix for sentence s_i . τ_{i, e_j, e_k} indicates the probability of emotion

transition from e_j to e_k for s_i . The transition probability from e_j to e_k in sentence s_i is determined by their Pearson coefficient weighted by the sum of the normalized emotion scores of e_j in s_{i-1} and e_k in s_i , which is defined as follows:

$$p(\tau_{i,e_j,e_k} | s_i, s_{i-1}, \lambda, \gamma) \propto \frac{\lambda_{e_j,e_k} + 1}{2} \times \left(\sum_{p=1}^{N_{s_{i-1}}} \frac{ES(w_p, e_j)}{N_{s_{i-1}}} + \sum_{q=1}^{N_{s_i}} \frac{ES(w_q, e_k)}{N_{s_i}} \right) + \gamma \quad (3)$$

A smoothing parameter $\gamma = 0.001$ is incorporated to avoid zero probabilities.

3.1.3. Generative Process

Based on the ψ_i and τ_{i,e_j,e_k} defined above, the topic-emotion transition probability is designed in the following ways: (1) If $\psi_i = 0$ and $j = k$, there is no change in either topic or emotion label for s_i ; (2) If $\psi_i = 1$ and $j = k$, the emotion label for s_i remains the same, but a new topic will be drawn under the same emotion label from θ_d . Therefore, $t_i \neq t_{i-1}$ and $e_i = e_{i-1}$; (3) If $\psi_i = 1$ and $j \neq k$, a new topic label and a new emotion label will be drawn from θ_d . As we expect that if the topic label stays the same, the emotion label would also stay the same, there is no definition for $\psi_i = 0$ and $j \neq k$. Therefore, the transition probability $p(e_i, t_i | \tau_{i,e_{i-1},e_i}, \psi_i, e_{i-1}, t_{i-1}, \theta, s_{i-1}, s_i, \epsilon, \lambda, \gamma)$ can be formally specified as,

$$\begin{cases} p(\psi_i = 0)p(\tau_{i,e_{i-1},e_i}), & \text{if } e_i = e_{i-1}, t_i = t_{i-1}, i \geq 2 \\ p(\psi_i = 1)p(\tau_{i,e_{i-1},e_i})\theta_{e_i,t_i}, & \text{if } e_i = e_{i-1}, t_i \neq t_{i-1}, i \geq 2 \\ p(\psi_i = 1)p(\tau_{i,e_{i-1},e_i})\theta_{e_i,t_i}, & \text{if } e_i \neq e_{i-1}, t_i \neq t_{i-1}, i \geq 2 \\ \theta_{e_i,t_i}, & \text{if } i = 1 \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

The overall generative process for TET is presented below:

- For each possible topic and emotion label combination (e, t) , draw $\varphi_{e,t} \sim Dir(\beta)$.
- For each document $d \in D$,
 - Draw topic-emotion proportion $\theta_d \sim Dir(\alpha)$.
 - For each sentence $s_i \in d$,
 - * If $i = 1$, set $\psi_i = 1$.
 - * Else
 - Calculate topic transition probability $p(\psi_i | s_i, s_{i-1}, s_{i+1}, \epsilon)$.
 - Calculate emotion transition matrix $p(\tau_{i,e_j,e_k} | s_i, s_{i-1}, \lambda, \gamma)$, $1 \leq j, k \leq E$.
 - * Perform block sampling (e_i, t_i) by $(e_i, t_i) \sim$

$$p(e_i, t_i | \tau_{i,e_{i-1},e_i}, \psi_i, e_{i-1}, t_{i-1}, \theta, s_{i-1}, s_i, \epsilon, \lambda, \gamma).$$
 - * Sample each word w_n in s_i , $w_n \sim Mul(\varphi_{e_i,t_i})$.

3.2. Parameter Estimation

In TET, the parameters can be estimated efficiently using the Expectation Maximization (EM) algorithm. As TET can be seen as a special type of HMM, the customized forward-backward algorithm and Viterbi algorithm in E-step of each iteration to accumulate the sufficient statistics and then update parameters in M-step are employed.

The latent variables in TET are the emotion label assignments e , the topic label assignments t , the emotion transition indicator τ and the topic transition indicator ψ . The combinations of $(e_i, t_i, \psi_i, \tau_i)$ at sentence s_i is considered as hidden states in our Markov chain of document d .

The parameters of TET needed to be updated iteratively are θ , φ and ϵ . The hyper-parameters α and β are set empirically and λ is pre-calculated incorporating the emotion correlations. Let $CD_{d,e,t}$ denote the total number of words in d associated with emotion label e and topic label t which are drawn from θ_d , $CW_{w,e,t}$ denote the number of times that word w is associated with the emotion label e together with the topic label t .

In E-step, the forward-backward algorithm along with Viterbi algorithm is executed and the following sufficient statistics are accumulated.

$$E[CD_{d,e,t}] = \sum_{i=1}^{m_d} p(e_i = e, t_i = t, \psi_i = 1 | d) N_{s_i} \quad (5)$$

$$E[CW_{w,e,t}] = \sum_{d=1}^{|D|} \sum_{i=1}^{m_d} \sum_{j=1}^{N_{s_i}} \delta(w_j = w) p(e_i = e, t_i = t | d) \quad (6)$$

$$E[\psi_i] = p(\psi_i = 1 | d), s.t. i \geq 2 \quad (7)$$

In M-step, the parameters θ , φ and ϵ are updated as follows,

$$\theta_{d,e,t} \propto E[CD_{d,e,t}] + \alpha \quad (8)$$

$$\varphi_{e,t,w} \propto E[CW_{w,e,t}] + \beta \quad (9)$$

$$\begin{aligned} \epsilon = \arg \max_{\epsilon} & \sum_d \sum_{i=1}^{m_d} E[\psi_i] \log p(\psi_i = 1 | d, \epsilon) \\ & + (1 - E[\psi_i]) \log (1 - p(\psi_i = 1 | d, \epsilon)), \end{aligned} \quad (10)$$

where ϵ is updated by optimizing a cross-entropy loss function via a gradient-based optimizer.

3.3. Emotion Lexicon Generation from the Training Data

In TET, an emotion lexicon is needed to calculate ES and initialize φ . We explored two ways of constructing the emotion lexicon.

One is based on an existing emotion lexicon, `cev`, provided in the Chinese emotional vocabulary ontology library¹. It contains seven top-level emotion categories including “*happy*”, “*good*”, “*angry*”, “*sad*”, “*fear*”, “*disgust*” and “*surprise*”. As the emotion categories in `cev` are not exactly the same as the emotion labels annotated in our data, they are aligned manually. Moreover, to accommodate uncertainties in emotion alignment, each term in `cev` is assigned with the score of 0.9 for its corresponding emotion category in `cev` and the remaining 0.1 is equally spread among all the other emotions categories. Emotion lexicon constructed in this way is referred to as `lex_cev`.

The other way is to construct the emotion lexicon from the training data, which is inspired by the lexicon generation method [32]. The emotion lexicon is represented as the term-by-emotion matrix. It can be derived by matrix multiplication between the term-by-document matrix and the document-by-emotion matrix, which can be easily constructed from the training data. For example, each document’s emotion labels in the training data corresponds to one row of the document-by-emotion matrix. As there are many ways of representing document such as raw frequencies, normalized frequencies, and term frequency-inverse document frequency (TF-IDF), three different emotion lexicons denoted by `lex_f`, `lex_nf` and `lex_tfidf` are constructed respectively.

4. Experiments

4.1. Setup

To evaluate the performance of the proposed approach for social emotion detection, we conduct experiments on the News Dataset 2016 (ND16) [7], which was collected from the social channel of Sina between January and December of 2016, consisting of 5,258 news documents with 6 reader emotions (i.e., *Touching*, *Anger*, *Amusement*, *Sadness*, *Shock* and *Curiosity*). The statistics are shown in Table 1. Following the same setup as in [7], the first 3,109 documents in chronological order are used for training and the rest 2,149 are for testing. Pre-processing is conducted on ND16 by first splitting each document into sentences through sentence boundary detection, then removing stop words, numbers, person names, punctuations and words appeared in less than 3 documents.

As mentioned before, λ_{e_j, e_k} is calculated based on Pearson correlation coefficient of emotions in the training set describing the degree of correlation between two emotion, which is shown in Figure 3. Dark color indicates that two emotions are positively correlated, e.g., *Shock* and *Curiosity*, while light color indicates that two emotions are negatively correlated, e.g., *Anger* and *Touching*. It is clear that the results are in line with our intuition, which justifies the incorporation of such information into our model.

Our TET model can output both document-level and sentence-level emotion labels. ND16 only contains news articles annotated with document-level

¹<http://ir.dlut.edu.cn/EmotionOntologyDownload/>

Table 1: Statistics of the News Dataset 2016 (ND16).

Emotion label	# of documents		# of votes	
	Train	Test	Train	Test
Touching	464	365	313,998	175,022
Anger	1077	831	835,644	583,826
Amusement	977	533	613,334	313,455
Sadness	393	293	331,450	230,035
Shock	123	93	292,523	160,670
Curiosity	75	33	133,995	66,682

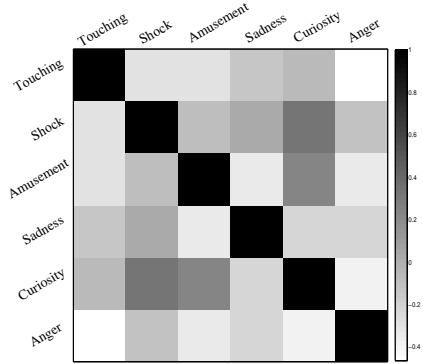


Figure 3: Gray-scale image of emotion correlations in the News Dataset 2016.

emotions from readers’ perspective. It is thus infeasible to use it to evaluate the accuracy of the sentence-level emotion detection of TET. Therefore, we use another corpus, RenCECps [33], which contains both the document-level and sentence-level emotion annotations. An example of an excerpt of a blog with its emotion annotations is presented in Table 2. It is worth mentioning that for both ND16 and RenCECps, only the document-level emotion annotations are used for training TET. The sentence-level emotion annotations of RenCECps are only used for performance evaluation of sentence-level emotion detection on the test set.

Table 2: An example of a part of one blog with its emotion annotation.

Document level	Joy:0.0 Hate:0.0 Love:0.0 Sorrow: 0.7 Anxiety: 0.7 Surprise: 0.0 Anger: 0.0 Expect: 0.0
Sentence 1: 这个问题真的很难回答，我忽然会在黄昏时陷入一种深深的沉思中。(This question is hard to answer, and I will suddenly fall in deep meditation in dusk.)	Joy:0.0 Hate:0.0 Love:0.0 Sorrow: 0.0 Anxiety: 0.9 Surprise: 0.0 Anger: 0.0 Expect: 0.0
Sentence 2: 不知道自己是在干什么，反而心里徒增一种孤独感，或许这种孤独就是落寞吧。(Do not know what I am doing, but feel lonely. Maybe such loneliness is desolation.)	Joy:0.0 Hate:0.0 Love:0.0 Sorrow: 0.8 Anxiety: 0.7 Surprise: 0.0 Anger: 0.0 Expect: 0.0

The RenCECps corpus contains 1,487 blog documents with 35,381 sentences. Each sentence is annotated with 8 basic emotions (i.e., *Joy*, *Hate*, *Love*, *Sorrow*, *Anxiety*, *Surprise*, *Anger* and *Expectation*), together with their emotion intensities as shown in Table 2. The statistics of RenCECps are presented in Table 3. The first 1,187 documents consisting of 27,528 sentences by chronological order are used for training and the rest 300 documents consisting of 7853 sentences are for testing. The emotion correlations in RenCECps are shown in Figure 4, which indicates *Hate* and *Anger* is highly positively related, and that *Love* and *Anxiety* is highly negatively related.

4.2. Baselines and Evaluation Metrics

The baselines can be roughly divided into two categories, classification models and topic-model based. Classification models can be further classified into three sub-categories, word-level based, optimization based, neural network based methods. Word-level based approaches include Emotion-Term model (ET) [23] and Supervised UnigrAm Model (SWAT) [34]. ET follows the Naïve Bayes method by assuming words are independently generated from social emotion classes. SWAT is a supervised approach using an uigram model trained to annotate emotion content. SOMM [7] is one of the optimization approaches which employs word embeddings to calculate word mover’s distance of all the documents via solving an optimization problem. ConstraintOp [17] employs

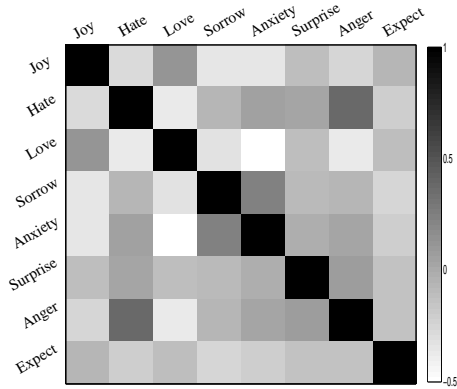


Figure 4: Gray-scale image of emotion correlations in RenCECps.

Table 3: Statistics of RenCECps.

Emotion label	number of documents		number of sentences	
	Train	Test	Train	Test
Joy	275	26	5766	899
Hate	110	0	2237	118
Love	345	108	6506	2636
Sorrow	145	91	4188	1754
Anxiety	121	44	4731	1918
Surprise	4	0	468	60
Anger	34	1	989	133
Expectation	153	30	2643	335

constraints such as emotion bindings and topic correlations for emotion detection from social media. The input features are generated using the traditional TF-IDF features or long short term memory (LSTM) network. Neural network based approaches include CNN [3, 4], CNN-SVM [5] and LSTM with attention [35]. The CNN uses CNN directly while CNN-SVM uses CNN to construct features first and then trains Support Vector Machine (SVM) based on the CNN-extracted features for emotion classification. LSTM with attention employs two kinds of attention mechanisms on top of word embeddings.

Topic models based approaches include JST, ASUM, ETM [23], CSTM [9], MSTM [8], SLTM [8] and the Affective Topic Model (ATM) [36]. JST assumes that each word is associated with a sentiment label and a topic label. ASUM assumes that each sentence is associated with a sentiment label and a topic label instead. ETM first generates a set of latent topics from emotions, followed by generating affective terms from each topic. CSTM distinguishes context-independent topics from both a background theme, which characterizes non-discriminative information, and a contextual theme, which characterizes context-dependent information across different collections. MSTM generates a

set of topics from words firstly, followed by sampling emotions from each topic. SLTM generates topics from social emotions directly. ATM is a multi-labeled topic model which is homologous to JST in generative process.

Two evaluation metrics are employed: accuracy at the top one prediction $Acc@1$ and averaged Pearson correlation coefficient over all documents AP . For a document d in the test set D , given the top one predicted emotion e_p^d , the top one ground truth emotion e_g^d , $Acc_d@1$ is defined as:

$$Acc_d@1 = \begin{cases} 1, & \text{if } e_p^d = e_g^d \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

$Acc@1$ can then be calculated by averaging $Acc_d@1$ over all documents.

For a document d in the test set D , given the predicted emotion distribution r_p^d and the ground truth emotion distribution r_g^d , AP is defined as

$$AP = \frac{1}{|D|} \sum_{d=1}^{|D|} \frac{\text{cov}(r_p^d, r_g^d)}{\sigma_{r_p^d} \sigma_{r_g^d}}, \quad (12)$$

where cov is the covariance and σ is the standard deviation.

4.3. Results

The overall performance of the proposed approach and the baselines on ND16 is shown in Table 4. For TET, the number of topics is set to 10 and the emotion lexicon `lex_nf` is used. For the baseline results reported here, the results of ConstraintOp and LSTM with attention were obtained by running the author published source code on our data. JST and ASUM results were generated based our adaptation of the published source code since both models were not for social emotion detection originally. For TET, JST and ASUM, the hyperparameter values, $\alpha = 0.01, \beta = 0.001, \gamma = 0.001$, were set empirically. JST and ASUM also used the same emotion lexicon as in TET for the incorporation of word prior emotion information. The results of other baselines are cited from [7] since we used the same dataset and the same experimental setup here.

It can be observed that TET outperforms all the other approaches on both $Acc@1$ and AP metrics. In specific, the word-level models assume words are independent from each other, with global document context ignored, while topic-model based approaches achieve better results with latent topics encoding document-level global context. However, none of them consider the associations of successive sentences. Neural network based methods perform better than word-level models but poorer than topic-model based approaches. However, the LSTM based method performs the worst. It might attribute to the complexity of the documents. LSTM based approaches, usually working on sentences, are unable to handle such long sequence. SOMM utilizes word embeddings to construct a network of documents, which take into consideration semantic correlations between words to some extent. Therefore, it performs slightly better than the best result in the category of topic-model based approaches. Still, it

Table 4: Overall performance of the proposed approach and the baselines on ND16.

Category		Approach	Acc@1(%)	AP
Discriminative	Word-level model	ET	48.04	0.43
		SWAT	38.97	0.40
	Neural network based	CNN-SVM	52.63	-
		CNN	51.23	-
		LSTM with attention	21.29	-
		ConstraintOp using TF-IDF features	28.21	0.21
	Optimization based	ConstraintOp using LSTM features	24.81	0.31
		SOMM	58.59	0.64
		Topic-model based	JST	58.33
	ETM		54.19	0.49
ASUM	43.16		0.39	
CSTM	40.74		0.43	
MSTM	32.17		0.34	
ATM	29.20		0.28	
SLTM	28.95		0.26	
Ours	TET	61.83	0.66	

dose not model the topic/emotion transitions directly. Instead, our proposed TET encodes topic/emotion transitions into the generative process of the topic model and thus achieves the best results overall.

To further investigate the performance of TET in comparison with JST and ASUM, experiments are conducted on ND16 using the same lexicon `lex.nf` with difference topic number settings. Figure 5 shows the performance of TET, JST and ASUM under topic numbers in $[1, 5, 10, 15, 20, 50]$. It can be observed that TET achieves better performance compared to JST and ASUM regardless of the topic number setting. It can also be observed that the performance of TET under different topic numbers is relatively stable while the results of JST and ASUM fluctuate greatly.

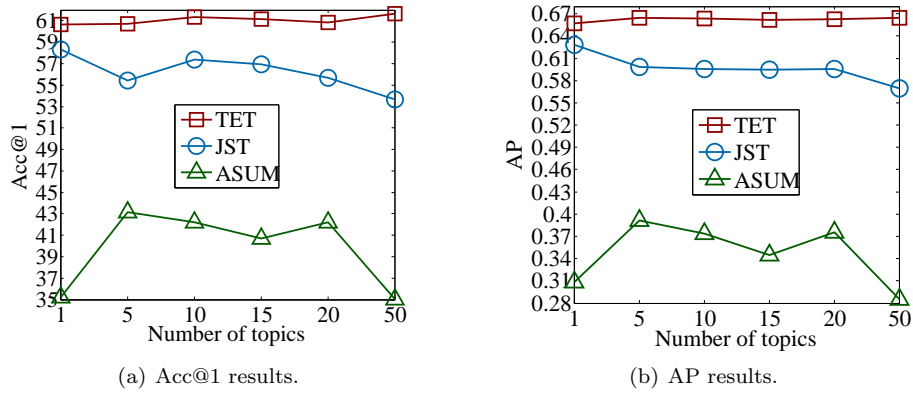


Figure 5: Performance comparison of TET, JST and ASUM with different number of topics on ND16.

4.3.1. Impact of Emotion Lexicon and Topic Number

We also investigate the performance of TET with different emotion lexicons and different topic numbers. Figure 6 shows the performance of TET on ND16 using different lexicons, such as `lex_nf`, `lex_f`, `lex_tfidf` and `lex_cev` under the topic number in [1, 5, 10, 15, 20, 50].

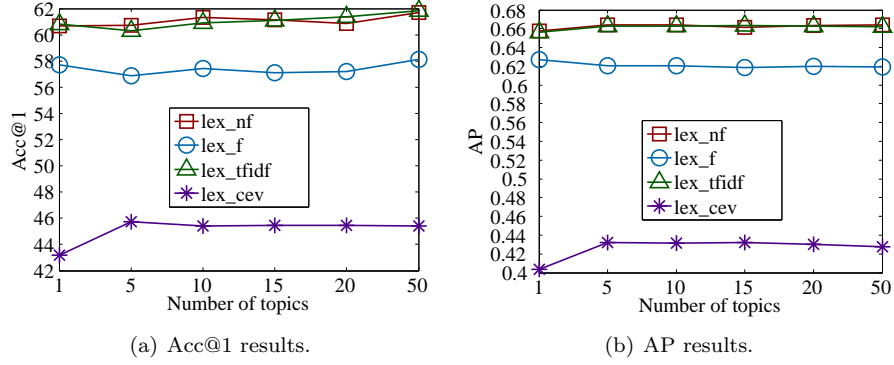


Figure 6: Performance of TET on ND16 using different emotion lexicons under different number of topics.

It can be observed that using the generated emotion lexicons from the training data, such as `lex_nf`, `lex_f` and `lex_tfidf`, TET achieves significantly better results compared to `lex_cev`. The worst results using `lex_cev` might be attributed to the indirect mapping of emotion categories and the differences of the data corpora used. As there is no one-to-one correspondence between the emotion categories in the emotion lexicon, `cev`, and the readers’ emotions in ND16, manual alignment of emotion categories might introduce some noises. Moreover, the data from which `cev` was derived and the social emotion dataset we used here are different. Therefore, it is more effective to automatically generate an emotion lexicon from our data directly. It can also be observed that the number of topics has less impact on the performance of TET although overall the best Acc@1 and AP results are obtained when the number of topics is set to 50.

4.3.2. Extracted topics

Apart from social emotion detection, TET can also extract topics from data. To evaluate the effectiveness of topics and emotions captured by TET, the top 10 words associated with the combination of one topic and one emotion extracted using Equation 9 are shown in Table 5. Under each of the six predefined emotions, two example topics are listed. It can be observed that most topics correspond to some events in social news. For example, topic 1 under the “*Touching*” emotion is about organ donation; topic 2 under the “*Amusement*” emotion is about live broadcasting on an online platform; topic 2 under the “*Shock*” emotion is about breast implant surgery. The topic results clearly

show the triggering events associated with certain social emotions.

Table 5: An example of topics extracted by TET under different emotions on ND16 dataset.

Touching		Anger		Amusement	
Topic 1	Topic 2	Topic 1	Topic 2	Topic 1	Topic 2
医院(hospital)	老师(teacher)	嫌疑人(suspect)	地铁(metro)	彩票(lottery)	直播(live broadcasting)
医生(doctor)	学生(student)	犯罪(commit crimes)	货车(truck)	家长(parents)	平台(platform)
手术(surgery)	救人(rescue)	现场(scene)	村民(villager)	照片(photo)	网络(network)
器官(organ)	帮助(help)	案件(case)	乘客(passenger)	红包(red packet)	主播(anchor)
照片(photo)	学习(learn)	公安局(public security bureau)	法院(court)	朋友(friend)	公司(company)
心脏(heart)	现场(scene)	报警(call the police)	现场(scene)	信息(message)	女孩(girl)
患者(patient)	跑(run)	派出所(police station)	司机(driver)	中奖者(winner)	粉丝(fan)
捐献(donate)	见义勇为(samaritan)	强奸(rape)	死亡(die)	奖金(bonus)	派出所(police station)
治疗(therapy)	爱心(love)	抓获(arrest)	被告人(defendant)	银行(bank)	女主播(amazon)
生命(life)	乡村(village)	交警(traffic police)	车厢(carriage)	工作人员(staff)	网站(website)
Sadness		Shock		Curiosity	
Topic 1	Topic 2	Topic 1	Topic 2	Topic 1	Topic 2
尸体(dead body)	现场(scene)	村民(villager)	手术(surgery)	春晚(Spring Festival Gala)	鱼(fish)
跳楼(jump from a building)	电梯(elevator)	蟒蛇(boa)	医生(doctor)	主持人(host)	大鱼(big fish)
走失(get lost)	事发(incident)	动物(animal)	隆胸(breast implant)	笑脸(smiling face)	渔民(fisherman)
爱(love)	小区(communitiy)	专家(specialist)	医院(hospital)	明星(star)	楠木(Phoebe zhenman)
喜欢(like)	死亡(die)	蟒(boa)	胸部(breast)	主持(preside over)	捕获(catch)
希望(hope)	救援(rescue)	无人区(depopped zone)	注射(injection)	观众(audience)	村民(villager)
狗狗(doggie)	火灾(fire)	保护(protect)	蛇头(ophicephalous)	央视(CCTV)	医生(doctor)
失踪(missing)	酒店(hotel)	蛇(snake)	果冻(jelly)	猴(monkey)	乌鸦(crow)
老家(hometown)	派出所(police station)	鳖(turtle)	篮球(basketball)	立体(stereoscopic)	保护(protect)
现场(scene)	跑(run)	徒步(on foot)	加拿大(Canada)	春节(Spring Festival)	金枪鱼(tuna)

For comparison purpose, we also show the most frequent words under each emotion found by [17] in Table 6. Compared to the topics extracted by TET, they are less meaningful. For example, under the “*Anger*” emotion, there are words such as hospital, school and driver. It is not obvious to find the relationship between the topic and the emotion, therefore can not really explain why the “*Anger*” emotion is evoked. On the contrary, words in the topics extracted by TET make it more easier to understand which events evoke the corresponding emotion.

Table 6: Most frequent words under different emotion labels found by [17] on ND16 dataset.

Touching	Shock	Amusement	Sadness	Curiosity	Anger
公司(company)	法院(court)	医院(hospital)	医院(hospital)	外孙(grandson)	医院(hospital)
现场(scene)	直播(live broadcasting)	公司(company)	现场(scene)	丹丹(dandan)	钱(money)
医院(hospital)	平台(platform)	现场(scene)	医生(doctor)	潘某(Pan)	学校(school)
医生(doctor)	钱(money)	女孩(girl)	女孩(girl)	女童(girl)	现场(scene)
员工(employee)	医院(hospital)	法院(court)	电话(phone)	小女孩(little girl)	电话(phone)
死亡(die)	死亡(die)	钱(money)	钱(money)	安检(security check)	学生(student)
夫妇(couple)	被告人(defendant)	电话(phone)	法院(court)	马艳玲(Ma Yanling)	报警(call the police)
王修(WangXiu)	被害人(victim)	工作人员(staff)	回家(go home)	陈俊伯(Chen Junbo)	派出所(police station)
身亡(die)	彩票(lottery)	事发(incident)	鉴定(authenticate)	救人(rescue)	司机(driver)
嫌疑人(suspect)	案件(case)	家属(family)	希望(hope)	村民(villager)	女孩(girl)

To further evaluate the effectiveness of emotion and topic transitions captured by TET, an example of a news article with the predicted topic-emotion transition results and its ground truth readers’ emotion votes are shown in Figure 7. It can be observed that not only the document-level emotions but also the sentence-level emotions can be detected simultaneously by the proposed TET with high accuracy.

4.4. Sentence-Level Emotion Classification

Since TET can also detect sentence-level emotions, we compare the performance of TET with JST and ASUM on the RenCECps corpus for sentence-level emotion detection. As JST does not assign emotion labels to sentences directly, the sentence-level emotion label of JST is obtained by aggregating the emotion-topic probabilities of words within each sentence. The detailed results of TET,

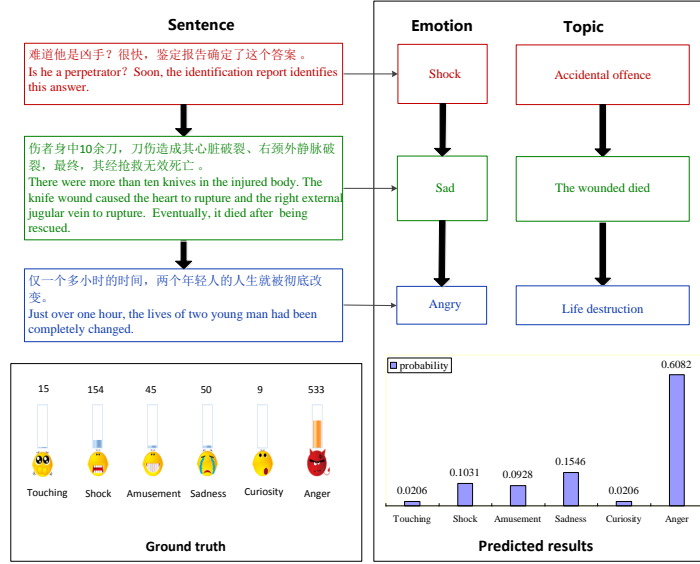


Figure 7: An example of a news article from Sina, its corresponding readers votes over predefined emotion classes, predicted document level and sentence level emotions.

JST and ASUM under different number of topics are shown in Figure 8. The emotion lexicon used is `lex_nf`. Moreover, we also conducted an experiment using LSTM with attention [35]. It adopts LSTM networks augmented with attention mechanisms for short-text emotion detection. The results of LSTM with attention were achieved by running the author published source code on our data set.

Table 7: Performance comparison on RenCECps.

Model	Acc@1	AP
JST	38.404	0.3138
ASUM	35.741	-0.1112
TET	41.908	0.3463
LSTM with attention	43.072	-

It can be seen from Table 7 and Figure 8 that TET achieves better performance compared with JST and ASUM on both metrics for sentence-level emotion classification. On *Acc@1*, JST and ASUM give similar results for topic numbers between 5 and 20. But ASUM gives the worst results on *AP*. LSTM with attention achieves the best performance on *Acc@1*. However, it should be mentioned that it is unfair to compare the proposed approach with the LSTM with attention approach since only document level annotations are employed in the proposed approach while the more grained sentence level annotations are needed by the LSTM with attention approach. It is also observed that the per-

performances of all the approaches on RenCECps are worse than those on ND16, except LSTM with attention. It is perhaps not surprising since sentence-level emotion classification is performed on sentences with limited content information. On the contrary, document-level emotion classification operates on the whole document and thus likely gives higher performance compared to classification on the finer-grained sentence level.

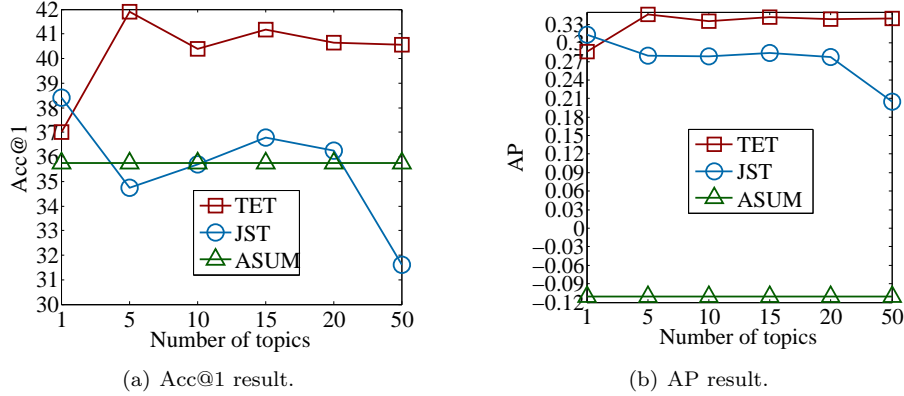


Figure 8: Performance comparison between TET, JST and ASUM with different number of topics on RenCECps.

5. Conclusions

In this paper, we have proposed the Topic-Emotion Transition (TET) model which models the transition of emotions and topics of successive sentences as a Markov chain. In TET, we used linguistic features of sentences to guide topic transition. Emotion correlations calculated from emotion lexicons automatically constructed from data is employed to guide emotion transitions. A customized forward-backward algorithm along with a Viterbi algorithm are used for inference and parameter estimation. Experiments show that our model outperforms the state-of-the-art methods in both document-level and sentence-level emotion classification.

Acknowledgments

We would like to thank the anonymous reviewers for their valuable comments and suggestions. This work was funded by the National Natural Science Foundation of China (61772132, 61528302), the National Key Research and Development Program of China (2016YFC1306704), the Jiangsu Natural Science Funds (BK20161430), the 333 Project of Jiangsu Province and Innovate UK (103652).

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