Proceedings of the Twenty-Fourth AAAI Conference on Artificial Intelligence (AAAI-10)

Sentiment Analysis with Global Topics and Local Dependency

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Abstract

With the development of Web 2.0, sentiment analysis has now become a popular research problem to tackle. Recently, topic models have been introduced for the simultaneous analysis for topics and the sentiment in a document. These studies, which jointly model topic and sentiment, take the advantage of the relationship between topics and sentiment, and are shown to be superior to traditional sentiment analysis tools. However, most of them make the assumption that, given the parameters, the sentiments of the words in the document are all independent. In our observation, in contrast, sentiments are expressed in a coherent way. The local conjunctive words, such as "and" or "but", are often indicative of sentiment transitions.

In this paper, we propose a major departure from the previous approaches by making two linked contributions. First, we assume that the sentiments are related to the topic in the document, and put forward a joint sentiment and topic model, i.e. Sentiment-LDA. Second, we observe that sentiments are dependent on local context. Thus, we further extend the Sentiment-LDA model to Dependency-Sentiment-LDA model by relaxing the sentiment independent assumption in Sentiment-LDA. The sentiments of words are viewed as a Markov chain in Dependency-Sentiment-LDA. Through experiments, we show that exploiting the sentiment dependency is clearly advantageous, and that the Dependency-Sentiment-LDA is an effective approach for sentiment analysis.

1. Introduction

With the development of Web 2.0, people can more easily express their views and opinions on the Web. They can post reviews at E-Commerce web sites, and express their opinions on almost everything in forums, blogs or other discussion groups. The opinion information they leave behind is important for both online industries and customers. By collecting the opinion information, companies can decide on their strategies for marketing and products improvement. Customers can make a better decision when purchasing products or services. Hence, in recent years, sentiment analysis has become a popular topic for many research communities, including artificial intelligence.

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In this paper, we focus on the task of sentiment classification, which classifies the sentiment orientation of an opinioned document (i.e. product review), as thumbs up (positive) or thumbs down (negative) (Pang and Lee, 2002; Turney, 2002; Blitzer et al, 2007). Here, we refer sentiment classification as the document-level sentiment classification, where sentiment is determined based on the overall sentiment orientation of an entire document. Most existing approaches (Pang and Lee, 2002; Cui et al, 2006; Blitzer et al, 2007) adopt supervised learning models, in which they are trained on annotated corpora of manually labeled documents. Several unsupervised learning approach have also been proposed (Turney, 2002; Liu 2010), where many are based on given sentiment lexicons.

The sentiment polarities are dependent on topics or domains. The same word may have different sentiment polarities in different domains. For instance, though the adjective 'complex' in the sentence, 'The movie is complex and great!', may have positive orientation in a movie review, it could also have negative orientation in a sentence, 'It is hard to use such a complex camera' in a electronic review. Therefore, it is more suitable to analyze the topic and sentiment simultaneously. Recently, various joint sentiment and topic models (Mei et al, 2007; Titov and McDonald, 2008; Lin and He, 2009) are proposed based on topic model (Blei et al, 2003; Hofmann, 1999). These methods view the text as a mixture of global topics, and they analyze the sentiment in the more detailed topic or domain level. However, they all assume that, given the parameters, the sentiments of the words in a document are independent, which is known as the "bag of words" assumption for topic model.

We present an extension of the topic model approach to sentiment analysis that is also a significant departure from the previous approach. We observe that the sentiment orientation of each word is dependent on the local context. The conjunctions play important roles on sentiment analysis (Ding and Liu, 2007). If the words or phrases are connected by conjunction "and", these words will belong to the same sentiment orientation. If the words or phrases

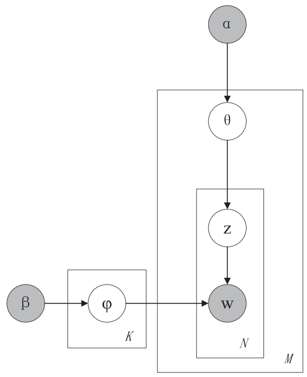

Figure 1. LDA

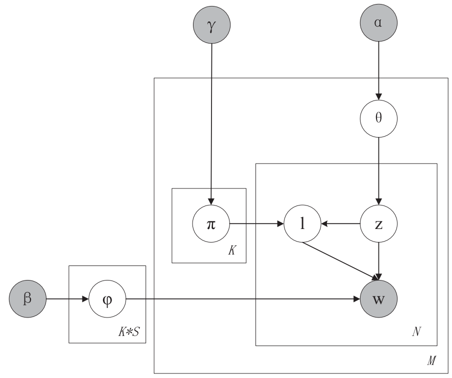

Figure 2. Sentiment-LDA

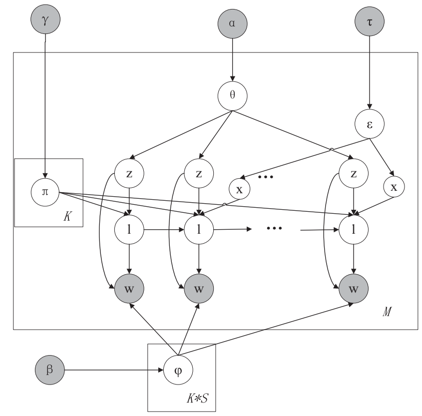

Figure 3. Dependency-Sentiment-LDA

are connected by conjunction “but”, these words or phrases will belong to different sentiment orientations. Meanwhile, from the linguistic views, the sentiment expressions are coherent. If these are no “but” or other adversative conjunctions in one sentence, the sentiment orientation will not change. Therefore, the assumption of sentiment independence for different words in a document, as assumed by many previous approaches we reviewed above, is not appropriate for sentiment analysis.

In this paper, we propose a joint sentiment and topic model, called Sentiment-LDA, by adding a sentiment layer to the Latent Dirichlet Allocation (LDA). Furthermore, to capture the dependency between the sentiments in the document, we propose a novel Dependency-Sentiment-LDA model by considering the inter-dependency of sentiments through a Markov chain. A major advantage is that the proposed Dependency-Sentiment-LDA not only analyzes the global topic and sentiment in a unified way, but also employs the local dependency among sentiments. To our best knowledge, this is the first work to incorporate sentiment dependency into joint sentiment and topic modeling. We conduct experiments to show that the proposed Dependency-Sentiment-LDA approach is an effective unsupervised method to sentiment classification

The rest of the paper is organized as follows: In Section 2, we present our Sentiment-LDA and Dependency-Sentiment-LDA. The model priors are described in Section 3. In Section 4, we introduce and discuss the experiment results. Section 5 introduces the related work. The conclusion and future work are presented in Section 6.

2. Dependency Sentiment Topic Model

In this section, we will introduce our two models for sentiment classification: Sentiment-LDA and Dependency-Sentiment-LDA

2.1 Sentiment-LDA

Sentiment classification aims to classify each opinioned document as positive or negative, based on its overall polarity. As described in previous section, the sentiment of a word is dependent on the domain or topic. It is appropriate to consider the sentiment and topic simultaneously. Moreover, besides the overall sentiment polarity of the document, people may be interested in the sub topics expressed in the document. Taking a movie review as an example, in addition to knowing the overall sentiment of the movie, we may interested in the “music”, “character”, or other sub-topics about this movie.

In order to model these observations, we propose a joint sentiment and topic model, Sentiment-LDA, which is an expansion of Latent Dirichlet Allocation (LDA). Figure 1 shows the LDA model. It contains three layers: document layer, topic layer and word layer. Sentiment-LDA, as shown in Figure 2, is a four-layer topic model. We add a sentiment layer between the topic layer and the word layer. The sentiment layer is associated with topic layer, and words are associated with both sentiment labels and topics. With this additional sentiment layer, the topic and sentiment are considered in a united way. Sentiment-LDA can not only classify the overall sentiment polarity for the document, but also can calculate the polarity for each topic.

Assume that we have a corpus with a collection of M documents denoted by $C = \{d_1, d_2, \cdots d_m\}$ each document in the corpus is a sequence of N_d words denoted by $d = \{w_1, w_2, \cdots w_{N_d}\}$, and each word in the document is an item from a vocabulary index with V distinct terms denoted by $\{1, 2, \dots, V\}$. Also, let K be the total number of topics, and S be the number of distinct sentiment labels. In this paper, the sentiment classification task only considers two categories: positive or negative. So we set S equal to 2, which means that l is a binary variable. If $l_i = 1$, the corresponding word contains more positive expression than negative, otherwise, $l_i = 0$. The procedure of generating a word w in document d has three stages. Firstly, one chooses a topic z from the document specific topic distribution θ_d. Following that, one chooses a sentiment label l from the sentiment distribution $\pi_{z,d}$, where $\pi_{z,d}$ is chosen conditioned on the topic label z. Finally, the word is chosen from the distribution $\varphi_{z,l}$ defined by both topic z and sentiment label l.

The formal definition of the generative process of Sentiment-LDA model is as follows:

1. For each document d, choose a distribution θ from $Dir(\alpha)$
2. For each topic z, under document d, choose a distribution $\pi_{d,z}$ from $Beta(\gamma)$
3. For each word w_i in document d
   3.1. Choose a topic z_i from $Multinomial(\theta)$
   3.2. Choose a sentiment label l_i from $Bernoulli(\pi_{d,z_i})$
   3.3. Choose a word w_i from the distribution over words defined by the topic z_i and sentiment label l_i, φ_{z_i,l_i}

2.2 Dependency-Sentiment-LDA

Sentiment-LDA is a joint sentiment and topic model. However, similar to previous methods, this model also makes an independent assumption among sentiment labels. In fact, sentiments are expressed in a coherent way.

Based on the above observations, we propose a novel model, called Dependency-Sentiment-LDA model, which drops sentiment layer independence assumption in Sentiment-LDA. As shown in Figure 3, the sentiments of the words in a document form a Markov chain, where the sentiment of a word is dependent on its previous one. The transition probability is related with z, π and transition variable x. The transition variable x determine where the corresponding sentiment label l comes from. If $x_i = 0$, a new sentiment label l_i is drawn from π_{d,z_i} with the corresponding z_i. If $x_i = 1$, the sentiment label l_i of i^{th} word is identical to the previous one l_{i-1}. If $x_i = -1$, the sentiment label l_i of i^{th} word is opposite to l_{i-1}, which shows that the sentiment changes from one polarity to the other. We hope to model that transition variable $x = 1$, when two words are connected by "and" or other related conjunctions; $x = -1$, when two words are connected by "but" or other adversative conjunctions . We will show how to add conjunction prior to Dependency-Sentiment-LDA in next section.

The definition of the generative process is as follows:

1. For each document d, choose a distribution θ from $Dir(\alpha)$, choose a distribution ε from $Dir\ (\tau)$
2. For each topic z, under document d, choose a distribution $\pi_{d,z}$ from $Beta(\gamma)$
3. For each word w_i in document d
   3.1 Choose a topic z_i from $Multinomial(\theta)$
   3.2 Choose a decision value x_i from $Multinomial(\varepsilon)$
   3.3 Choose a sentiment label l_i as the following rules:
      a) If $x_i = 1$, $l_i = l_{i-1}$
      b) If $x_i = -1$, $l_i = -(l_{i-1})$
      c) If $x_i = 0$, l_i from $Bernoulli(\pi_{d,z_i})$
   3.4 Choose a word w_i from the distribution over words defined by the topic z_i and sentiment label l_i, φ_{z_i,l_i}

2.3 Inference

In this section, we describe the inference algorithms for Sentiment-LDA and Dependency-Sentiment-LDA. The Gibbs Sampling is adopted here for the inference task.

In order to perform Gibbs sampling with Sentiment-LDA, we need to compute the conditional probability, $P(z_i = z, l_i = l \mid z_{-i}, l_{-i}, w)$, where z_{-i} and l_{-i} are vectors of assignments of topics and sentiments for all the words in the collection except for the considered word at position i in document d. Due to space limit, we show the sampling formulas without derivation:

$$P(z_i = z, l_i = l \mid z_{-i}, l_{-i}, w) \propto \frac{\left\{n_m^{(z)}\right\}_{-i} + \alpha}{\{n_m\}_{-i} + K\alpha} * \frac{\left\{n_m^{(z,l)}\right\}_{-i} + \gamma_l}{\left\{n_m^{(z)}\right\}_{-i} + \sum_{l=1}^{S}\gamma_l} * \frac{\left\{n_{z,l}^{(t)}\right\}_{-i} + \beta}{\{n_{z,l}\}_{-i} + V\beta}$$

Where $n_m^{(z)}$ is the number of times words assigned to topic z in document m. n_m is the total number of words in document m. $n_m^{(z,l)}$ is the number of times words assigned to topic z and sentiment l in document m. $n_{z,l}^{(t)}$ is the number of times word i appeared in topic z and sentiment l. $n_{z,l}$ is the number of times words assigned to topic z and sentiment l. the subscript $-i$ denotes a quantity except for the data in position i.

For Dependency-Sentiment-LDA, we need to consider the defined Markov property when computing the conditional probability. We formulate the Dependency-Sentiment-LDA as a special type of HMM. The word layer is considered as the observation, and the combination of sentiment layer and transition variable layer, in condition of topic layer, is considered as hidden variables. Due to space limit, we just show you the sampling formulas without detailed derivations. When $x_i \neq 0$ and $x_{i+1} \neq 0$, legal component i , which satisfies our defined Markov property, is sampled as follows:

$$P(x_i = x, z_i = z, l_i = l \mid x_{-i}, z_{-i}, l_{-i}, w) \propto \frac{\left\{n_m^{(z)}\right\}_{-i} + \alpha}{\{n_m\}_{-i} + K\alpha} * \frac{\left\{n_{z,l}^{(t)}\right\}_{-i} + \beta}{\left\{n_{z,l}\right\}_{-i} + V\beta} * \frac{\left(\left\{n_m^{(x_i)}\right\}_{-i} + \tau_{x_i}\right)}{\left(\{n_m\}_{-i} + \sum_{x=1}^{X}\tau_x\right)} * \frac{\left(\left\{n_m^{(x_{i+1})}\right\}_{-i} + I(x_i = x_{i+1}) + \tau_{x_{i+1}}\right)}{\left(\{n_m\}_{-i} + \sum_{x=1}^{X}\tau_x + 1\right)}$$

Where $n_m^{(x)}$ is the number of transition variables assigned to x in document m; $I(\cdot)$ is the indicator function. Other formulas can be acquired in the similar way.

With the above samples, the model parameters θ, π, φ can be estimated as:

$$\theta_m^{(z)} = \frac{n_m^{(z)} + \alpha}{n_m + K\alpha} \quad (1)$$

$$\varphi_{z,l}^{(t)} = \frac{n_{z,l}^{(t)} + \beta}{n_{z,l} + V\beta} \quad (2)$$

$$\pi_m^{(z,l)} = \frac{n_m^{(z,l)} + \gamma_l}{n_m^{(z)} + \sum_{l=1}^{S} \gamma_l} \quad (3)$$

We analyze the subtopic in the document by $\theta_m^{(z)}$, the sentiment polarity of subtopic by $\pi_m^{(z,l)}$, the overall sentiment polarity of entire document is calculated as follows

$$P(s = l|d = m) = \sum_{z=1}^{K} \theta_m^{(z)} * \pi_m^{(z,l)} \quad (4)$$

3. Defining the Prior Knowledge

The prior knowledge will guide the Sentiment-LDA and Dependency-Sentiment-LDA models with what the sentiments and transitions should look like in the data set.

Tabel 1. Sentiment Lexicons Description

	Lexicon Name	Neg. Size	Pos. Size	Description
1	HowNet	2700	2009	English translation of positive/negative Chinese words
2	SentiWordNet	4800	2290	Words with a positive or negative score above 0.6
3	MPQA	4152	2304	MPQA subjectivity lexicon
4	Intersection	411	308	Words appeared in all 1, 2, and 3
5	Union	9361	5305	Words appeared in 1 or 2, or 3

3.1 Sentiment Prior

The sentiment prior knowledge is obtained from sentiment lexicons. We use several types of sentiment lexicons to analyze the impact of sentiment prior. Table 1 shows the lexicons we use in our experiments. HowNet is a knowledge database in Chinese, and provides an online English translation word list with positive and negative tags. SentiWordNet (Esuli and Sebastiani, 2006)) and MPQA (Wilson et al. 2005) are also popular lexical resources for sentiment analysis. We also take the union and intersection, respectively, of the above three lexicons.

3.2 Transition Prior

Transition variable prior knowledge is mainly obtained by analyzing the conjunctive words. We collect a number of conjunctions, and divide them into two types: one is called coordinating conjunctions, such as “and”, which maintain the expressed sentiment orientation; the other is adversative conjunctions, such as “but”, which change the expressed sentiment orientation.

3.3 Incorporating the Prior Knowledge

In the experiments, the prior knowledge is utilized during the initialization and iteration steps for Gibbs Sampling. For sentiment prior knowledge, the initialization starts by comparing each word token in corpus against the words in sentiment lexicons. If there is a match, the corresponding sentiment label is assigned to the word token. Otherwise, a sentiment label is randomly sampled for a word token. We also add the pseudo count for corresponding sentiment in iteration step. The utilization of transition prior is similar as the sentiment prior.

4. Experiments

4.1 Experiment Setup

We use the Amazon product review data set from (Blitzer et al, 2007). The data set contains four types of products: books, DVDs (mainly about movie), electronics and kitchen appliances. There are totally 4000 positive and 4000 negative reviews. The data set is processed as follows: the punctuation and other non-alphabet words are removed first; then we stem all the words; finally, the stopwords are also removed. The final performance is measured in terms of accuracy.

Since our proposed models are unsupervised, we design sentiment lexicons based method as our baseline. Given a review, we first count the number of positive words and the number of negative words based on the sentiment lexicons, which are listed in Table 1. If the number of positive words is larger than the number of negative words, the review is considered as positive, otherwise as negative. We also compare our results with the results acquired by supervised method presented in (Denecke,2009).

4.2 Experiment Results

Tabel 2. Experiment Results with different lexicons

Sentiment prior	Lexicon based Method	Sentiment-LDA	Dependency-Sentiment-LDA
HowNet	56.3%	62.1%	66.5%
SentiWordNet	57.2%	60.6%	64.2%
MPQA	60.2%	65.3%	**69.0%**
Intersection	57.1%	59.7%	65.1%
Union	59.7%	62.3%	67.3%
Supervised Classification (Denecke 2009)		**Best Accuracy: 70.7%**	

Table 2 shows the experimental results with different sentiment lexicons. The performance of Sentiment-LDA is better than the lexicon based methods. The lexicon based methods achieve the accuracy around 56%~60%. The accuracy for the Sentiment-LDA is around 60%~65%. This is because the sentiment lexicons are designed for general application, it maybe not suitable for the product domain. With joint sentiment and topic analysis, our Sentiment-LDA can detect the topic and sentiment in a unified way. Hence, it can improve the sentiment classification accuracy.

Dependency-Sentiment-LDA is more powerful than Sentiment-LDA. Dependency-Sentiment-LDA can not only analyze the topic and sentiment simultaneously, but also consider the local dependency among sentiment labels. By incorporating the sentiment dependency, the accuracy is improved by 3%~5%, which shows the effectiveness of the sentiment dependency. The best result is achieved with our proposed Dependency-Sentiment-LDA.

The sentiment lexicons with larger number of entries may be potentially better than the smaller lexicons. The union of lexicons achieves a better result than the intersection of lexicons. But it is not always the case. MPQA achieves the best result among all lexicons. This may be because MPQA lexicon is suitable for this product review set, which shows that the domain-specific lexicons are important for sentiment analysis.

Our model is competitive as an unsupervised method. The best result achieved by Dependency-Sentiment-LDA is 69.0%, which is comparable to 70.7% achieved by supervised method (Denecke, 2009) in the same data set. Moreover, the result 70.7% is achieved based on 10-fold cross validation in a test set comprising of only 800 reviews. Our results are achieved on the whole product review set with 8000 reviews.

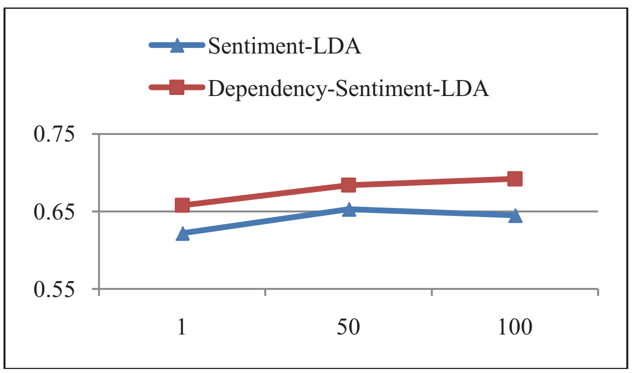

Figure 4. Accuracy with different topic numbers

We also analyze the influence of topic numbers. We use MPQA as the sentiment prior. Figure 4 shows the experiment results. When the number of topic is set to 1, the model is degraded into the traditional unigram model for topic layer, which ignores the topic-sentiment correlation. The overall performance increases, when multiple topics are considered, which also proves that it is appropriate to analyze the topic and sentiment in a unified way.

4.3 Examples of Selected Topics

A topic is multinomial distribution over words conditioned on topics and sentiments. The top words (most probable words) for each distribution could approximately reflect the meaning of the topic. Table 3 shows the selected examples of global topics extracted with our models. The top two rows are topics extracted with Sentiment-LDA. The bottom two rows are topics extracted with Dependency-Sentiment-LDA. Each row shows the top 20 words for corresponding topic. Even the topics are all about DVD-movie with positive (Pos) and negative (Neg) polarity. We can find that the topics extracted by Dependency-Sentiment-LDA are more clear and informative.

Table 3. Extracted Topic Examples: DVD-movie

Sentiment-LDA	**Pos**	star, come, don, just, mage, movie, set, kid, isn, pick, sound, want, dvd, feature, awaken, maybe, setting, good, dome, aren
	Neg	movie, film, scene, character, watch, end, plot, actor, feel, really, bad, act, think, come, story, try, war, guy, make, play
Dependency-Sentiment-LDA	**Pos**	movie, best, great, dvd, john, action, favorite, good, want, collection, worth, include, dance, actor, star, better, enjoy, film, documentary, story
	Neg	movie, film, worst, bad, scene, fight, adrian, just, buy, maybe, act, dead, air, actor, say, didn, music, suck, watch, man

Our proposed models can classify the overall sentiment of entire review as formula (4). It also can extract the topics expressed in the reviews as formula (1), and identify the sentiment polarity of these topics as formula (3). For example, an electronic product review is labeled as negative in the data set. Our proposed model can correctly classify it as negative. Besides, our model can find that the review mainly expresses two topics (the probability for other topics is below 0.1). One maybe about "usage"; the other may be about "sound" (from the top words for corresponding topic). The model also indentifies that the first topic is expressed more positive and the second topic is expressed more negative in this review.

5. Related Work

Sentiment analysis is the computational study of opinions, sentiments and emotions expressed in text. One of the most studied tasks is sentiment classification, see the tutorials (Liu, 2010; Pang and Lee, 2009). Topic model (Blei et al, 2003; Hofmann, 1999) is a type of unsupervised method. It views each document as mixture of topics. Currently, these are various topic models on sentiment analysis. We call this type of model as joint sentiment and topic model. Topic-Sentiment Model (TSM) (Mei et al, 2007) jointly models the mixture of topics and sentiment predictions. However, TSM is essentially from probabilistic Latent Semantic Indexing (pLSI) (Hofmann, 1999), thus suffers from the problems of inference on new document and over fitting data. Multi-Grain Latent Dirichlet Allocation model (MG-LDA) (Titov and McDonald, 2008) is argued to be more appropriate to build topics that are representative of ratable aspects of objects from online user reviews, by allowing terms being generated from either a global topic or a local topic. But MG-LDA is still purely topic based without considering the associations between topics and sentiments. Joint Sentiment/Topic (JST) model (Lin and He, 2009) detects sentiment and topic simultaneously from text. It is a four-layer topic model, which is similar to our Sentiment-LDA. However, JST puts the sentiment layer corresponding to document layer, which is hard to analyze the sentiment of sub topics. Sentiment-LDA puts sentiment layer corresponding to topic layer, which is easy to analyze the sentiment for both document and document sub topics.

Moreover, all of previous joint sentiment and topic models employ “bag of words” assumption, which assume that, given the parameters, sentiments of words in the document are independent. Our proposed Dependency-Sentiment-LDA drops this assumption. We view sentiments of all words in the document as a Markov chain. We also add the sentiment lexicon and conjunction words as the model prior. Although there are some studies on topic model beyond bag-of-words (Griffiths et al, 2005; Wallach, 2006; Gruber et al, 2007; Jiang, 2009), as far as we know, this is the first work to model the sentiment dependency in the joint sentiment and topic methods.

6. Conclusions and Future Work

In this paper, we investigate the sentiment dependency in joint sentiment and topic analysis. A novel model, called Dependency-Sentiment-LDA, is proposed with extension of our joint sentiment and topic model, Sentiment-LDA. Dependency-Sentiment-LDA model relaxes the sentiment independent assumption. It not only analyzes the global topic and sentiment in a unified way, but also employs the local dependency among sentiments. To the best of our knowledge, this is the first work to model sentiment dependency for topic model. The experiment results demonstrate the effectiveness of our models. In the future work, we will expand our joint sentiment and topic models for more complicated tasks in sentiment analysis, such as rating classification or sentiment summarization.

Acknowledgement

This work was partly supported by the Chinese Natural Science Foundation under grant No.60973104 and No. 60803075, and carried out with the aid of a grant from the International Development Research Center, Ottawa, Canada. We also thank the anonymous reviewers, Qixia Jiang, Zhiwei Li, Jing Jiang, Yunbo Cao and Qiang Yang for their helpful comments.

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