Topic and Sentiment Unification Maximum Entropy Model for Online Review Analysis

Changlin Ma
School of Computer
Central China Normal University
Wuhan, Hubei 430079, China
+862767868318
clma@mail.ccnu.edu.cn

Meng Wang
School of Computer
Central China Normal University
Wuhan, Hubei 430079, China
+862767868318
mcl89@163.com

Xuewen Chen
Department of Computer Science
Wayne State University
Detroit, MI 48202, USA
+13135776783
xwchen@wayne.edu

ABSTRACT

Opinion mining is an important research topic in data mining. Many current methods are coarse-grained, which are practically problemic due to insufficient feedback information and limited reference values. To address these problems, a novel topic and sentiment unification maximum entropy LDA model is proposed in this paper for fine-grained opinion mining of online reviews. In this model, a maximum entropy component is first added to the traditional LDA model to distinguish background words, aspect words and opinion words and further realize both the local and global extraction of these words. A sentiment layer is then inserted between a topic layer and a word layer to extend the proposed model to four layers. Sentiment polarity analysis is done based on the extraction of aspect words and opinion words to simultaneously acquire the sentiment polarity of the whole review and each topic, which leads to, fine-grained topic-sentiment abstract. Experimental results demonstrate the validity of the proposed model and theory.

Categories and Subject Descriptors

H.2.8 [**Database Management**]: Database Applications *–Data mining*; I.2.7 [**Artificial Intelligence**]: Natural Language Processing *–Language generation, Language models.*

General Terms

Design, Performance, Languages.

Keywords

LDA, Topic and sentiment unification, Maximum entropy, Fine-grained opinion mining.

1. INTRODUCTION

With the development of the Internet, tens of thousands of users began to purchase various products and services through the network and publish the related online reviews. Analysis of these reviews can not only help potential customers make an intelligent decision, but also guide enterprises to timely improve the quality of their products and services. However, the number of online reviews is enormous, which is impractical, if not impossible, to use traditional manual-methods for fast access. Therefore, it has been an important research topic for researchers to develop opinion mining of online reviews through automatic analyzing and extracting methods.

Current studies [1-3] showed that review opinion mining mainly included the following tasks: (1) extracting the aspect and opinion words; (2) sentimental classification and polarity analysis; and (3) generating sentiment abstract. In addition, in terms of the granularity, current methods mainly focused on three levels: word or phrase level, sentence level, and chapter level.

Previous efforts on opinion mining focused on sentiment classification on chapter and sentence levels. Pang et al. [4-5] firstly made a series of studies about polarity classification. Three classifiers, Naive Bayes Model (NBM), Maximum Entropy Model (MaxEnt), and Support Vector Machines (SVM), were mainly used [4]. Graph-based minimum-cut approach was adopted to identify the subjectivity and objectivity of sentences in [5]. Ni et al. [6] employed NBM, SVM, and Roechio's algorithm to make text sentiment classification. Information Gain and CHI were also used to select features [6].

Nevertheless, the aforementioned studies are all coarse-grained methods, where only the overall sentiment polarity can be derived [7]. In practical reviews, consumers usually hold different sentiment opinion towards different topics. It is more helpful for potential consumers to simultaneously acquire the overall and specific comments of products or services. In this context, traditional opinion mining methods were unable to meet the practical needs and consequently, fine-grained methods emerge as an alternative, which involves more specific sentiment classification on word or phrase level.

Another issue in sentiment analysis is that the same word may have distinct sentiment orientations in the contexts with different topics. For example, the word "simple" is positive in the sentence "The restaurant has simple tones", which means that the restaurant style is simple and elegant. However, it is negative in the sentence "The food tastes simple", which denotes poor food taste. Therefore, it is essential to integrate the context with topics in sentiment analysis.

In recent years, many scholars applied Latent Dirichlet Allocation model (LDA) to opinion mining. Standard LDA is a bag-of-word model, which assumes that a document is a set of independent words. Locations and semantic information of words are not considered in the model. Thus, it is not appropriate for word

WWW 2015 Companion, May 18–22, 2015, Florence, Italy.
ACM 978-1-4503-3473-0/15/05.
http://dx.doi.org/10.1145/2740908.2741704

extraction in fine-grained methods [8]. Some researchers extended LDA model and generated topic or sentiment labels on sentence level [9-10], which had achieved good performance.

In this paper, a topic and sentiment unification maximum entropy LDA model (TSU MaxEnt-LDA) is proposed for fine-grained opinion mining. Topics and sentiments are simultaneously considered on word or phrase level to get more specific sentiment polarity analysis. In Section 2, we briefly review some related work. This is followed by the proposed work in Section 3. In Section 4, we present some experimental results.

2. RELATED WORK

LDA and extended work played a significant role in opinion mining research. Titov et al. [8] presented Multi-Grain LDA model (MG-LDA) and Multi-Aspect Sentiment model (MAS). Brody et al. [9] extended LDA to Local-LDA on sentence level. Experiments showed that these three models were very useful for the extraction of topics, which could acquire both global aspect words and local aspect words. Nevertheless, aspect words and opinion words were not distinguished in these models, which would lead to low accuracy of sentiment analysis.

To overcome the shortcomings of standard LDA in extraction of fine-grained features, Zhao et al. [10] added a maximum entropy (MaxEnt) component in LDA models and proposed a MaxEnt-LDA model. Considering the location and semantic information of words, two indicator variables were introduced to distinguish local and global aspect words and opinion words. Topics were generated on sentence level. In this case, words had the same topic with their sentences. However, sentiment analysis was not involved in their research.

Mei et al. [11] proposed Topic Sentiment Mixture model (TSM) in which topic and sentiment were separated from each other by assuming that sentiment words had no impact on topic identification. In realistic applications, however, this assumption does not hold as sentiment words are an important part to express topic.

A Joint Sentiment/Topic model (JST) was presented in [12] to sample topic and sentiment labels for each word. JST adopted standard LDA, which was not suitable for fine-grained feature extraction. Based on JST, Jo et al. [13] proposed Aspect Sentiment Unification Model (ASUM). Different from JST, the location and semantic information of words were considered in ASUM for sampling topic and sentiment labels. However, the two models all made sentiment analysis on the whole review level, which could not obtain more fine-grained sentiment polarity.

Through inserting sentiment layer between topic layer and word layer, Li et al. [14] proposed Sentiment-LDA to extend traditional LDA from three-layer to four-layer. The sentiment polarities of the whole review and each topic were simultaneously obtained. However, this model still adopted bag-of-word structure.

Considering the aforementioned disadvantages, TSU MaxEnt-LDA is proposed in this paper for fine-grained opinion mining. Referring to MaxEnt-LDA and considering location and semantic information of words, maximum entropy component is added in TSU MaxEnt-LDA. A sentiment layer is inserted between topic layer and word layer to extend the proposed model from traditional three layers to four layers. Under the assumption that each sentence just belongs to one topic and one sentiment, sentiment polarity analysis is done based on the extraction of aspect words and opinion words to simultaneously acquire the sentiment polarity of the whole review and each topic. Finally, fine-grained topic-sentiment abstract can be extracted.

3. TSU MAXENT-LDA DESCRIPTIONS

The following example is used to describe the terminology of TSU MaxEnt-LDA.

"The food is great. The salad is delicious. The waiter is quite friendly. The staff is great. Beijing restaurant is great. The restaurant has simple tones. The food tastes simple."

In this review, "delicious" and "salad" have strong association, so do "friendly" and "waiter". Local opinion words "delicious" and "friendly" can be used to modify local aspect words "salad" (an aspect of topic "food") and "waiter" (an aspect of topic "staff"). Global aspect words are collective nouns denoting distinguished products or service entity, such as "Beijing Restaurant" and "Hilton Restaurant" in "restaurant" domain. Global opinion words, like "great", are usually used to modify various topics and global aspect words, such as food, staff and Beijing restaurant. Background words are used to connect aspect and opinion words. Global words and background words have higher occurrence ratio than local words, which will disturb the identification of local words. Compared with the comments of the whole review, potential consumers prefer to obtain the evaluation of specific aspects. Therefore, local words should be solely identified.

Furthermore, opinion word "simple" is positive in the sentence "The restaurant has simple tones", which means that the restaurant style is elegant. However, it is negative in the sentence "The food tastes simple", which indicates bland food. Hence, sentiment orientation is dependent on topics and a same word may have different sentiment polarities in different cases.

In this paper, we assume that each sentence just belongs to one topic and sentiment and each word has same topic and sentiment with its sentence. In sentiment classification, we consider two kinds of sentiment orientations (positive and negative) and take the sentiment polarity with bigger probability value.

3.1 Generating Process of TSU MaxEnt-LDA

TSU MaxEnt-LDA is an extension of MaxEnt-LDA. It incorporates both topic and sentiment, which is shown in Figure 1. Maximum entropy component is added in TSU MaxEnt-LDA to distinguish background words, aspect words and opinion words and further realize both the local and global extraction of these words. Two indicator variables, y and u, are introduced to distinguish word categories ({0，1，2}, where 0: background word, 1: aspect word, 2: opinion word) and word types ({0，1} 0: local, 1: global). The Meanings of notations are listed in Table 1.

In TSU MaxEnt-LDA, the generative process is as follows.

1. For a corpus,
(1) Draw word distributions $\Phi \sim Dir(\beta)$ (background word: Φ^{B}, global aspect word: $\Phi^{A,g}$, global opinion word: $\{\Phi^{O,g,s}\}$, local aspect word: $\{\Phi^{A,t,s}\}$, local opinion word: $\{\Phi^{O,t,s}\}$ (s=0, 1 t=1，.....，T).
(2) Draw word type distribution $\rho \sim Beta(\eta)$.

2. For each document d in the corpus,
(1) Draw the document's topic distribution $\theta^{d} \sim Dir(\alpha)$.

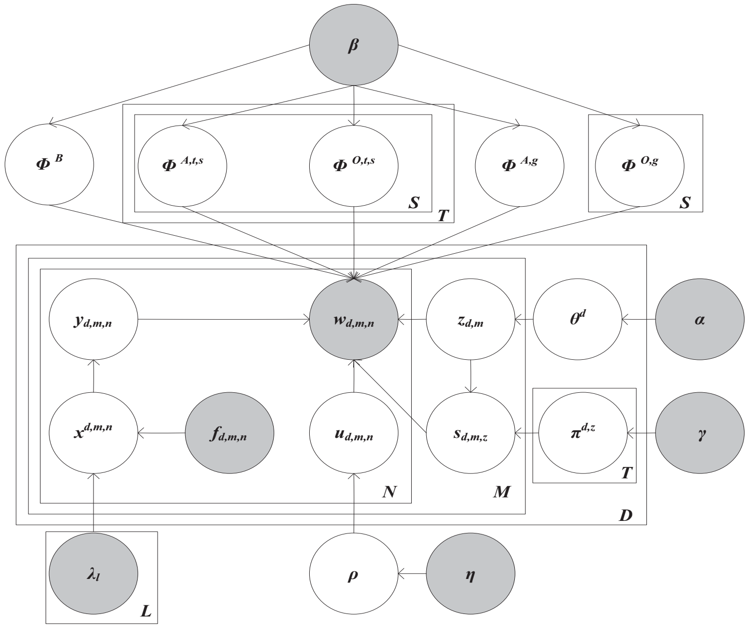

Figure 1. TSU MaxEnt-LDA model

Table 1. Meanings of the notations in TSU MaxEnt-LDA

Notations	Meanings
D	the number of reviews
M	the number of sentences
N	the number of words
T	the number of topics
S	the number of sentiments
W	the word list representation of the corpus
V	the vocabulary size
L	the number of categories for words
w	word
z, t	topic,{1，.....，T}
s	sentiment,{0，1}（0: negative;1: positive）
y	Word-category indicator variable
u	Word-type indicator variable
f	feature vector set
θ	Dirichlet distribution over topics
Φ	Dirichlet distribution over words
π	Beta distribution over sentiments
ρ	Beta distribution over word-types
α, β	Dirichlet prior vectors for θ, Φ
γ, η	Beta prior vectors for π, ρ

(2) For each topic z in the document, draw a sentiment distribution $\boldsymbol{\pi}^{d,z}$~$Beta(\gamma)$.

3. For each sentence m in document d,
(1) Choose a topic $z_{d,m}$ from $Multinomial(\theta^d)$.
(2) Given topic $z_{d,m}$, choose a sentiment $s_{d,m,z}$ from $Bernoulli(\boldsymbol{\pi}^{d,z})$.

4. For each word n in sentence m ($w_{d,m,n}$),
(1) Draw the topic $z_{d,m}$ and sentiment $s_{d,m,z}$ of word $w_{d,m,n}$ which accord with its sentence according to the assumption.
(2) Choose a word-type $u_{d,m,n}$ from $Bernoulli(\rho)$ over {0，1}.
(3) Choose a word-category $y_{d,m,n}$ from a multinomial distribution over {0，1，2} parameterized by $\boldsymbol{x}^{d,m,n}$. How to set $\boldsymbol{x}^{d,m,n}$ will be discussed in Section 3.2.
(4) Generate $w_{d,m,n}$ as follows:

$$w_{d,m,n} \sim \begin{cases} Multi(\Phi^{B}) & if\left(y_{d,m,n}=0\right) \\ Multi(\Phi^{A,t,s}) & if\left(y_{d,m,n}=1, u_{d,m,n}=0\right) \\ Multi(\Phi^{A,g}) & if\left(y_{d,m,n}=1, u_{d,m,n}=1\right) \\ Multi(\Phi^{O,t,s}) & if\left(y_{d,m,n}=2, u_{d,m,n}=0\right) \\ Multi(\Phi^{O,g,s}) & if\left(y_{d,m,n}=2, u_{d,m,n}=1\right) \end{cases}$$

3.2 Inference

Researches [9-10, 15-16] have shown that simple POS features are very effective for distinguishing aspect words and opinion words. In MaxEnt-LDA, they used previous, current and next POS tags features. Similar to MaxEnt-LDA, we also use a maximum entropy model in TSU MaxEnt-LDA and apply it to the feature vector $f_{d,m,n}$ of $w_{d,m,n}$ to set $\boldsymbol{x}^{d,m,n}$. Different from method in [10], we regroup POS features and select features as follows: $\{POS_{i-1}, POS_i, POS_{i+1}, POS_{i-1}POS_i, POS_iPOS_{i+1}, POS_{i-1}POS_iPOS_{i+1}\}$. The feature of $w_{d,m,n}$ is denoted as $f_{d,m,n}=\{pos_{n-1}, pos_n, pos_{n+1}, pos_{n-1}pos_n, pos_npos_{n+1}, pos_{n-1}pos_npos_{n+1}\}$. Then we can get λ_l of $f_{d,m,n}$ from MaxEnt model which is trained by a set of training sentences with labeled background, aspect and opinion word. $x_1^{d,m,n}$ can be obtained from the following equation.

$$P(y_{d,m,n}=l \mid f_{d,m,n}) = x_1^{d,m,n} = \frac{exp(\lambda_l \cdot f_{d,m,n})}{\sum_{l'=0}^{2} exp(\lambda_{l'} \cdot f_{d,m,n})},$$

where $l \in \{0,1,2\}$. In this paper, we use Maximum Entropy Toolkit [17], which is used by most researchers. We use Gibbs sampling to estimate the latent variables ρ, θ, π, and Φ of TSU MaxEnt-LDA model. The notations are described in Table 2.

Table 2. Meanings of the notations in inference

Z_{-m}	the topic assignments for all sentences except sentence *m*
S_{-m}	the sentiment assignments for all sentences except sentence *m*
$N^{d}_{(t)}$	the number of sentences assigned to topic *t* in document *d*
$N^{d}_{(\cdot)}$	the number of sentences in document *d*
$N^{d}_{(t,s)}$	the number of sentences assigned to topic *t*, sentiment *s* in document *d*
$N^{A,t,s}_{(v)}$	the number of times word *v* is assigned as a local aspect word to topic *t*, sentiment *s*
$N^{A,t,s}_{(\cdot)}$	the total number of times any word is assigned as a local aspect word to aspect *t*, sentiment *s*
$N^{O,t,s}_{(v)}$	the number of times word *v* is assigned as a local opinion word to topic *t*, sentiment *s*
$N^{O,t,s}_{(\cdot)}$	the total number of times any word is assigned as a local opinion word to aspect *t*, sentiment *s*
$N^{A,g}_{(v)}$	the number of times word *v* is assigned as a global aspect word
$N^{A,g}_{(\cdot)}$	the total number of times any word is assigned as a global aspect word
$N^{O,g,s}_{(v)}$	the number of times word *v* is assigned as a global opinion word to sentiment *s*
$N^{O,g,s}_{(\cdot)}$	the total number of times any word is assigned as a global opinion word to sentiment *s*
$m^{A,t,s}_{(v)}$	the number of times word *v* is assigned as a local aspect word to topic *t*, sentiment *s* in sentence *m* of document *d*
$m^{A,t,s}_{(\cdot)}$	the total number of times any word is assigned as a local aspect word to aspect *t*, sentiment *s* in sentence *m* of document *d*
$m^{O,t,s}_{(v)}$	the number of times word *v* is assigned as a local opinion word to topic *t*, sentiment *s* in sentence *m* of document *d*
$m^{O,t,s}_{(\cdot)}$	the total number of times any word is assigned as a local opinion word to aspect *t*, sentiment *s* in sentence *m* of document *d*
N^{B}_{v}	the number of times word $w_{d,m,n}$ or word *v* is assigned as a background word
$N^{B}_{(\cdot)}$	the total number of times any word is assigned as a background word
$N^{A}_{(0)}$	the number of times any word is assigned as a local aspect word
$N^{A}_{(1)}$	the number of times any word is assigned as a global aspect word
$N^{A}_{(\cdot)}$	the total number of times any word is assigned as an aspect word
$N^{O}_{(0)}$	the number of times any word is assigned as a local opinion word
$N^{O}_{(1)}$	the number of times any word is assigned as a global opinion word
$N^{O}_{(\cdot)}$	the total number of times any word is assigned as an opinion word

All these counts represented by *N* variables exclude sentence *m* of document *d*. The topic and sentiment of sentence *m* in document *d* are drawn from the conditional probability

$$p\left(z_{d,m}=t, s_{d,m}=s \mid \boldsymbol{z_{-m}}, \boldsymbol{s_{-m}}, \boldsymbol{w}, \boldsymbol{y}, \boldsymbol{u}, \boldsymbol{f}\right) \propto \frac{N^{d}_{(t)}+\alpha}{N^{d}_{(\cdot)}+T\alpha} \times \frac{N^{d}_{(t,s)}+\gamma}{N^{d}_{(t)}+S\gamma}$$
$$\times \left(\frac{\Gamma(N^{A,t,s}_{(\cdot)}+V\beta)}{\Gamma(N^{A,t,s}_{(\cdot)}+m^{A,t,s}_{(\cdot)}+V\beta)} \prod_{v=1}^{V} \frac{\Gamma(N^{A,t,s}_{(v)}+m^{A,t,s}_{(v)}+\beta)}{\Gamma(N^{A,t,s}_{(v)}+\beta)} \right) \cdot$$
$$\times \left(\frac{\Gamma(N^{O,t,s}_{(\cdot)}+V\beta)}{\Gamma(N^{O,t,s}_{(\cdot)}+m^{O,t,s}_{(\cdot)}+V\beta)} \prod_{v=1}^{V} \frac{\Gamma(N^{O,t,s}_{(v)}+m^{O,t,s}_{(v)}+\beta)}{\Gamma(N^{O,t,s}_{(v)}+\beta)} \right)$$

The approximate probability of word-type *u* assigned as aspect words in corpus is

$$\rho^{A}_{u} = \frac{N^{A}_{(u)}+\eta}{N^{A}_{(\cdot)}+2\eta}$$

The approximate probability of word-type *u* assigned as opinion words in corpus is

$$\rho^{O}_{u} = \frac{N^{O}_{(u)}+\eta}{N^{O}_{(\cdot)}+2\eta}$$

The approximate probability of topic *t* in document *d* is

$$\theta^{d}_{t} = \frac{N^{d}_{(t)}+\alpha}{N^{d}_{(\cdot)}+T\alpha} \cdot$$

The approximate probability of topic *t* for sentiment *s* in document *d* is

$$\pi^{d}_{t,s} = \frac{N^{d}_{(t,s)}+\gamma_{s}}{N^{d}_{(t)}+S\gamma_{s}} \cdot$$

The approximate probability of word *v* assigned as a local aspect word to topic *t* and sentiment *s* is

$$\Phi^{A,t,s}_{v} = \frac{N^{A,t,s}_{(v)}+\beta}{N^{A,t,s}_{(\cdot)}+V\beta} \cdot$$

The approximate probability of word *v* assigned as a local opinion word to topic *t* and sentiment *s* is

$$\Phi^{O,t,s}_{v} = \frac{N^{O,t,s}_{(v)}+\beta}{N^{O,t,s}_{(\cdot)}+V\beta} \cdot$$

Then the following equations are used to jointly sample values for $y_{d,m,n}$ and $u_{d,m,n}$.

$$p\left(y_{d,m,n}=0 \mid \boldsymbol{z}, \boldsymbol{s}, \boldsymbol{y_{-(d,m,n)}}, \boldsymbol{u_{-(d,m,n)}}, \boldsymbol{w}, \boldsymbol{f}\right)$$
$$\propto \frac{exp(\lambda_{0} \cdot f_{d,m,n})}{\sum_{l'=0}^{2} exp(\lambda_{l'} \cdot f_{d,m,n})} \frac{N^{B}_{w_{d,m,n}}+\beta}{N^{B}_{(\cdot)}+V\beta} \quad .$$

$$p\left(y_{d,m,n}=l, u_{d,m,n}=b \mid \boldsymbol{z}, \boldsymbol{s}, \boldsymbol{y_{-(d,m,n)}}, \boldsymbol{u_{-(d,m,n)}}, \boldsymbol{w}, \boldsymbol{f}\right)$$
$$\propto \frac{exp(\lambda_{l} \cdot f_{d,m,n})}{\sum_{l'=0}^{2} exp(\lambda_{l'} \cdot f_{d,m,n})} \cdot g(w_{d,m,n}, z_{d,m}, s_{d,m,z}, l, b) \quad .$$

where $1 \le v \le V, 1 \le t \le T, s \in \{1,2\}, l \in \{1,2\}, b \in \{0,1\}$. $g(v,t,s,l,b)$ is defined as follows:

$$g(v,t,s,l,b) = \begin{cases} \dfrac{N^{A,t,s}_{(v)}+\beta}{N^{A,t,s}_{(\cdot)}+V\beta} \cdot \dfrac{N^{A}_{(0)}+\eta}{N^{A}_{(\cdot)}+2\eta} & if\ l=1, b=0 \\ \dfrac{N^{O,t,s}_{(v)}+\beta}{N^{O,t,s}_{(\cdot)}+V\beta} \cdot \dfrac{N^{O}_{(0)}+\eta}{N^{O}_{(\cdot)}+2\eta} & if\ l=2, b=0 \\ \dfrac{N^{A,g}_{(v)}+\beta}{N^{A,g}_{(\cdot)}+V\beta} \cdot \dfrac{N^{A}_{(1)}+\eta}{N^{A}_{(\cdot)}+2\eta} & if\ l=1, b=1 \\ \dfrac{N^{O,g,s}_{(v)}+\beta}{N^{O,g,s}_{(\cdot)}+V\beta} \cdot \dfrac{N^{O}_{(1)}+\eta}{N^{O}_{(\cdot)}+2\eta} & if\ l=2, b=1 \end{cases} .$$

4. EXPERIMENTS

In this paper, we use the same data set as Brody and Zhao did in [9, 10], which originates from [7, 18, 19]. Similar to their methods, we manually annotate 50 sentences for training the MaxEnt model. When pre-processing the data, we remove stop words and use Standford POS Tagger [20] to tag the data set. We also back up an original data version for extracting the contextual features.

Referring to the parameter setting in [10, 13, 21], we use Gibbs sampling and set parameters as follows: iterating times=500, α=50/T , β=0.1 , γ=1 , η =0.5, where γ is symmetric and γ=1means all sentiment distributions have the same probability. This kind of parameter setting is proved by experiments to reach the best performance.

Similar to the experimental methods in [7, 9, 10], the number of topics is set as T=14 and we manually classify them into six topics (Food, Service, Price, Ambience, Anecdotes, Miscellaneous) from which three major topics (Staff, Food, and Ambience) are selected for evaluating the performance of TSU MaxEnt-LDA model.

In the experiments, we firstly distinguish aspect words and opinion words. Based on this, the local and global extraction of these words is realized. Then sentiment polarity classification of TSU MaxEnt-LDA is done and topic-sentiment abstract can be concluded, which is shown in Table 3 (P: probability of positive sentiment, N: probability of negative sentiment). The sampling results of aspect words and opinion words in MaxEnt-LDA are shown in Table 4. The two tables all select the top 10 words for corresponding topic.

Table 3. Sampling results of TSU MaxEnt-LDA

Food				Staff			
P (78.23%)		N (21.77%)		P (58.53%)		N (41.47%)	
Aspect	Opinion	Aspect	Opinion	Aspect	Opinion	Aspect	Opinion
food	delicious	food	hot	service	ok	service	evil
dessert	tasty	rice	cooked	waiter	great	waiter	incompetent
cake	missed	turkey	bland	man	excellent	staff	not
chocolate	fresh	sushi	horrible	staff	extremely	problem	unprofessional
dish	authentic	chicken	raw	people	friendly	manager	never
coffee	good	dumpling	awful	waitress	competent	hostess	back
wine	really	burger	oily	manager	helpful1	times	slow
rice	virginia	toast	forgot	bartender	attentive	waitress	lousy
bread	satisfying	chow	ordinary	member	nice	guy	rude
sauce	decent	pancakes	disgusting	guy	professional	member	ask
Ambience				**General Opinion**		**General aspect**	
P (75.29%)		**N (24.71%)**		**P (67.25%)**	**N (32.75%)**		
Aspect	Opinion	Aspect	Opinion				
place	recommend	decor	small	great	bad	America	
bar	wonderful	area	crowded	nice	not	NYC	
atmosphere	nice	seat	loud	excellent	never	New York	
seat	love	table	tiny	recommend	would	restaurant	
decor	fun	place	dark	best	back	Italian	
area	romantic	space	noise	special	terrible	country	
dining	feel	outdoor	not	love	awful	NY	
music	beautiful	scene	annoying	good	forget	spot	
space	cozy	atmosphere	traffic	ok	better	deli	
brunch	comfortable	Bar	feel	amazing	wish	experience	

Table 4. Sampling results of MaxEnt-LDA

Food		Staff		Ambience		General Opinion
Aspect	Opinion	Aspect	Opinion	Aspect	Opinion	
chocolate	good	service	friendly	room	small	good
desert	best	staff	attentive	dining	nice	well
cake	great	food	great	tables	beautiful	nice
cream	delicious	wait	Nice	bar	romantic	great
ice	sweet	waiter	good	place	cozy	better
desserts	hot	place	excellent	decor	great	small
coffee	amazing	waiters	helpful	scene	open	bad
tea	fresh	restaurant	rude	space	warm	worth
bread	tasted	waitress	extremely	area	feel	definitely
cheese	excellent	waitstaff	slow	table	comfortable	special

From table 3, we can see that local aspect words under each topic are quite representative and coherent and local opinion words under each topic highly accord with corresponding topics. Furthermore, the global opinion words and aspect words are all correctly clustered under the corresponding categories.

Comparing Table 3 with Table 4, we can see that the extraction results of aspect words and opinion words are similar. However, there is not sentiment classification in Table 4. Obviously, adding sentiment component into TSU MaxEnt-LDA model makes the classification results in Table 3 more informative and helpful for users.

The quantitative evaluation method of the sentiment orientation in [14] is used to analyze the overall sentiment of reviews. We calculate the accuracy to judge the validity of overall sentiment analysis through the following equation:

$$Accuracy = \frac{N'}{N_{total}}.$$

where N' is the number of correctly predicted reviews, N_{total} is the total number of reviews. The accuracy values of TSU MaxEnt-LDA, ASUM [13], and Sentiment-LDA [14] are shown in Table 5. Sentiment-LDA and ASUM all added sentiment seed words which interfered with the experimental results. Hence, the sentiment seed words are not adopted in our experiments. We can see that TSU MaxEnt-LDA achieves the highest accuracy among three models. It is more effective of our model to sample topic and sentiment label for each sentence than of Sentiment-LDA to sample topic and sentiment label for each word. In addition, over 80% of the labeled sentences in the data set [7] have one topic and sentiment label, which confirms our assumption that a sentence usually belongs to an aspect and a sentiment. Compared with ASUM, both TSU MaxEnt-LDA and Sentiment-LDA obtain more fine-grained sentiment distribution of topics and reach higher sentiment classification accuracy.

Table 5. Accuracy values of three models

Model	Restaurants
Sentiment-LDA	53.62%
ASUM	25.63%
TSU MaxEnt-LDA	62.26%

5. REFERENCES

[1] Pang, B. and Lee, L. 2008. Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval*. 2, 1 (Feb. 2008), 125-135.

[2] Inui, T. and Okumura, M. 2006. A survey of sentiment analysis. *Journal of natural language processing.* 13, 3 (2006), 201-241.

[3] Li, J. 2013. Summary of product reviews opinion mining, *Modern Computer*. 5 (2013), 11-16.

[4] Pang, B., Lee, L., and Vaithyanathan, S. 2002. Thumbs up? Sentiment classification using machine learning techniques. *In Proceedings of the ACL-02 conference on Empirical methods in natural language processing*. Association for Computational Linguistics. 10, 1 (2002), 79-86.

[5] Pang, B. and Lee, L. 2004. A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts, *Proceedings of the 42nd annual meeting on Association for Computational Linguistics*: *Association for Computational Linguistics*. (2004), 271-278.

[6] Ni, X., Xue, G. R., Ling, X., Yu, Y., and Q. Yang. 2007. Exploring in the Weblog space by detecting informative and affective articles. *In Proc. of the 16th Int. Conf. on World Wide Web*. (2007), 281-290.

[7] Ganu, G., Elhadad, N., and Marian A. 2009. Beyond the stars: Improving rating predictions using review text content. *In WebDB*. (2009).

[8] Titov, I. and McDonald, R. 2008. Modeling online reviews with multi-grain topic models. *In Proceeding of the 17th International Conference on World Wide Web*. ACM. (2008), 111-120.

[9] Brody, S. and Elhadad, N. 2010.An unsuper-vised aspect-sentiment model for online reviews. *In Proceedings of Human Language Technologies: The Annual Conference of the North American Chapter of the Association for Computational Linguistics*. (2010), 804-812.

[10] Zhao, X., Jiang, J., Yan, H., and Li, X. 2010. Jointly modeling aspects and opinions with a MaxEnt-LDA hybrid. *In Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing*. Cambridge, MA, (2010). Association for Computational Linguistics, 56-65.

[11] Mei, Q., Ling, X., Wondra, M., Su, H., and Zhai,C. 2007. Topic sentiment mixture: modeling facets and opinions in weblogs. *In Proceedings of the 16th international conference on World Wide Web* (2007). ACM, New York, NY, USA, 171-180.

[12] Lin, C. and He, Y. 2009. Joint sentiment/topic model for sentiment analysis. *In Proceeding of the 18th ACM conference on Information and knowledge management* (2009). ACM, New York, NY, USA, 375-384.

[13] Yohan, J. and Alice H. O. 2011. Aspect and sentiment unification model for online review analysis. *Proceedings of the fourth ACM international conference on Web search and data mining* (2011). ACM, 815-824.

[14] Li, F. T., Huang, M. L., and Zhu X. Y. 2010. Sentiment Analysis with Global Topics and Local Dependency, *Proceedings of the Twenty-Fourth AAAI Conference on Artificial Intelligence*. AAAI 2010.

[15] Hu, M. Q. and Liu, B. 2004. Mining and summa-rizing customer reviews. *In Proceedings of the 10th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (2004). ACM, 168-177.

[16] Jin, W. and Ho, H. H. 2009. A novel lexicalized HMM-based learning framework for web opinion mining. *In Proceedings of the 26th International Conference on Machine Learning*. (2009), 465-472.

[17] https://github.com/lzhang10/maxent

[18] http://people.dbmi.columbia.edu/noemie/ursa

[19] http://newyork.citysearch.com

[20] http://nlp.stanford.edu/software/tagger.shtml

[21] Griffiths, T. L. and Steyvers, M. 2004. Finding scientific topics, *Proceedings of the National Academy of Sciences of the United States of America*. 101, suppl. 1, (2004), 5228-5235.