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Detecting bursts in sentiment-aware topics from social media

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ABSTRACT

Nowadays plenty of user-generated posts, e.g., sina weibos, are published on the social media. The posts contain the public's sentiments (i.e., positive or negative) towards various topics. Bursty sentiment-aware topics from these posts reveal sentiment-aware events which have attracted much attention. To detect sentiment-aware topics, we attempt to utilize Joint Sentiment/Topic models, these models are achieved with Latent Dirichlet Allocation (LDA) based models. However, most of the existing sentiment/topic models cannot be directly utilized to detect sentiment-aware topics on the posts, since applying the models to the posts directly suffers from the context sparsity problem. In this paper, we propose a Time-User Sentiment/Topic Latent Dirichlet Allocation (TUS-LDA) which simultaneously models sentiments and topics for posts. Thereinto, TUS-LDA aggregates posts in the same timeslices or from the same users as pseudo-documents to alleviate the context sparsity problem. Based on TUS-LDA, we further design an approach to detect bursty sentiment-aware topics and these sentiment-ware topics can reflect bursty real-world events. Experiments on the Chinese sina weibos show that TUS-LDA outperforms previous models in the tasks of sentiment classification and burst detection in sentiment-aware topics. Finally, we visualize the bursty sentiment-aware topics discovered by TUS-LDA.

1. Introduction

With the rapid growth of Web 2.0, a mass of user-generated posts, e.g., sina weibos, are published on the social media. These posts capture people's interests, thoughts, sentiments and actions, and have been accumulating on the social media over a long period. The topically similar posts, gathered at a certain time period with specific sentiment polarities, reveal the general public's interest. A sudden increase of these posts usually indicates a burst of interest about current events, e.g., the negative event, earthquake, or the positive event, the announcement of mobile phone. These events are always coupled with specific sentiments. Hence, finding bursty sentiment-aware topics can benefit us to monitor the most popular sentiment-aware topics which can affect the public. In this paper, we aim to work on mining sentiment-aware topics from posts. We further study to detect bursts from these sentiment-aware topics.

Topic modeling [1–3] and sentiment analysis [4,5] on the posts are complementary. Thereinto, sentiments on the posts are sensitive to topics, and topics in the posts often imply the sentiments of the public. Thus, jointly modeling topics and sentiments on the posts can reflect people's sentiments on different topics. For example, we can obtain a sentiment-aware topic, e.g., an topic about "Sinking of Dongfangeve Zhi Xing" {{东方星(Dongfangxing), 长江(Yangtze River), 客船(Passenger Ship), 沉船(Shipwrecks), 遇难者(Victims), 客轮(Passenger Ship), 翻沉(Sinking), 遗体(Remains), 遇难(Murdered) and 搜救(Rescue)} with the overall sentiment polarity "negative". However, unlike the normal documents (e.g., news and long reviews), the posts on the social media are short and informal. Thus, they often lack rich contextual information. However, conventional methods of modeling topics and sentiments mainly depend on the document-level contextual information. Hence, the task of topic modeling and sentiment analysis on the posts become more challenging than that of modeling topics and sentiments analysis on normal documents.

Topic models, e.g., LDA [1,6] and pLSA [7], originally focus on mining topics from lengthy texts, and they can further be extended to extract sentiments. Conventional sentiment-aware topic models, like Joint Sentiment/Topic Model (JST) [8] and Aspect/Sentiment Unification Model (ASUM) [9], are utilized for uncovering the hidden topics and sentiments from text corpus. In JST and ASUM, each document is a mixture of sentiment/topics and each sentiment/topic is a mixture of words. Thereinto, each sentiment label

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(a) Announcement of iPhone SE (b) Apple products

Fig. 1. (a) A temporal topic (b) A stable topic.

in the models is viewed as a special kind of topic, i.e., topics are unknown and data-driven while sentiments are known and specified. Since the posts are short and informal and they often lack rich contextual information, applying the models to the short posts on the social media directly suffers from the context sparsity problem.

One simple and effective way to alleviate the sparsity problem is to aggregate the short posts into lengthy pseudo-documents [10,11]. Hence, we assume that the posts on the social media is a mixture of two kinds of topics: (1) temporal topics which are related to current events (e.g., posts about a topic "Announcement of iphone SE" in Fig. 1(a) which are published in a short time), (2) stable topics which are related to personal interests (e.g., posts about a topic "Apple products" in Fig. 1(b) which are published by a user). In these posts, temporal topics are sensitive to time and related to specific sentiments. For example, when an event occurs, posts with specific sentiments about the event may burst in a short period within a large volume. Hence, if posts talk about temporal topics, all these posts in the same timeslice are aggregated as pseudo-documents and these pseudo-documents are mixtures of sentiment-aware topics. Moreover, stable topics are related to specific users, where each user focuses on several topics with specific sentiments. Hence, if posts talk about stable topics, all these posts published by the same users are aggregated as pseudo-documents and these pseudo-documents are also mixtures of sentiment-aware topics. We assume that posts on social media belong to two kinds of topics, temporal topics and stable topics. Temporal topics are sensitive to time and are generated from posts in the same timeslices. Stable topics are related to users and are generated from posts published by the same users. Thus, if a post belongs to a temporal topic, then it is assigned to a sentiment-aware topic in its corresponding timeslice; if a post belongs to a stable topic, it is assigned to a sentiment-aware topic in its corresponding user.

Based on the analysis of the characteristics of topics and sentiments, Zhao et al. [11] have an important observation of topics: A single post always talks about a single topic. Furthermore, according to Kiritchenko et al. [12] and Lu et al. [13], although a post usually talks about a single topic, it may talk about multiple fine-grained aspects of the topic with different sentiment polarities. For a post, it may express only a kind of sentiment, e.g., the post "It is a good day" is positive, and it can also express more than one kind of sentiments, e.g., the post "Lily looks nice, but Tom does not." contains both positive and negative sentiments [14]. Thus, to accurately model sentiment polarities for the posts, we follow the observations in [12,13] and assume that words in a single post can correspond to multiple sentiment polarities.

To model the association between each post's sentiments and topics, we further assign a sentiment label to each post. The sentiment label represents the overall sentiment polarities of the post and is determined by the sentiment polarities of words in the post. If the words in a post express both positive and negative sentiments, the overall sentiment polarities of the post should be judged based on the stronger one [14].

To handle the aforementioned problems, our work is based on a Time-User Sentiment/Topic Latent Dirichlet Allocation (TUS-LDA) [15], which utilizes user and timeslice information to aggregate posts to alleviate the context sparsity problem. Moreover, TUS-LDA models topics and sentiments based on the characteristics of topics and sentiments. Specifically, the sentiments of a post and the words in the post are all drawn from document-level sentiment distribution; within the chosen sentiment of the post, the topic of the post is drawn from a user-level or timeslice-level sentiment/topic distribution.

In this paper, we utilize TUS-LDA to mine sentiment-aware topics from posts and then detect bursts from sentiment-aware topics discovered by TUS-LDA. In TUS-LDA, we can not only capture the sentiment-aware topics from posts, but also monitor the variations of sentiment-aware topics over time. Our work focuses on the variations of sentiment-aware topics over time to detect and track bursty sentiment-aware topics. These topics are often triggered by real-world events. When a negative event "东方之星号客轮翻沉事件" ("Sinking of Dongfang zhi Xing")[1] occurred, the volume of weibos about the negative event sent spiked to more than 5000 times per second. An effective way to detect bursts is using bursty features, e.g., the bursty volumes in posts corresponding to the same topics [19], in data streams. In our work, we consider detecting bursts by monitoring the variations of sentiment-aware topics over time. Different from the work on detecting bursty topics in [10,16], we consider to detect bursts on sentiment-aware topics. Because there is a strong correlation between bursty topics and public moods, there are always bursty sentiments within the bursty events [17]. For example, negative words "害怕" ("scared") and "伤心" ("sad") emerge with a large volume after an earthquake occurs. Thus, we detect new bursty events by monitoring states of sentiments and topics in weibos. To detect the bursts in sentiment-aware topics, we propose to apply Kleinberg's [18,19] modeling of bursts to sentiment-aware topics discovered by TUS-LDA.

Compared with our previous work [15], there are three new contributions added in this work:

[1] "东方之星号客轮翻沉事件" ("Sinking of Dongfang zhi Xing"): The ship which was traveling on the Yangtze River in Jianli, Hubei Province with 454 people on board was capsized by a severe thunderstorm on June 1, 2015.

1) We further describe and interpret our proposed model, Time-User Sentiment/Topic Latent Dirichlet Allocation (TUS-LDA). TUS-LDA aggregates posts in the same timeslice or from the same user as a pseudo-document to alleviate the context sparsity problem, and models topics and sentiments based on the characteristics of topics and sentiments.
2) We discuss the related work of burst detection and propose an approach to detect bursts in sentiment-aware topics discovered from the posts with TUS-LDA.
3) We conduct experiments on a chinese sina weibo dataset to evaluate the effectiveness of sentiment classification and burst detection in sentiment-aware topics which are discovered by TUS-LDA and visualize bursty sentiment-aware topics.

The rest of the paper is organized as follows: in Section 2, we introduce the related work about topic models on short texts and joint sentiment/topic models; in Section 3, we give the definitions of the basic terminologies we will use in this paper; in Section 4 we present our model TUS-LDA and the method of burst detection in sentiment-aware topics; Experimental settings and results are shown in Section 5. Finally, in Section 6, we conclude this paper and discuss the future work.

2. Related work

LDA [1] and PLSA [7] originally focus on mining topics from lengthy documents.

2.1. Topic models with user or time

Daud et al. [20] proposed Conference Mining(ConMin) based on Latent Dirichlet Allocation, which modeled documents from conference level. ConMin can discover topically related conferences, conferences correlations and conference temporal topic trends. Furthermore, they [21] also proposed a Temporal-Author-Topic model(TAT) to simultaneously model text, researchers and publishing time, where they used author, not document, to model topics and utilized time to bias topic distributions. In TAT, they aimed to mine the topically interest (topic distribution θ) of each author. And they can use them to discover similar authors based on their interested topics. Moreover, they can mine word distributions ϕ and time distributions ψ. TAT can only mine the time where topics occurs based on ψ, but it cannot model the variations of topic volumes over time. Hence, bursty topics cannot be mined by TAT. Different from TAT, our work aims to introduce time and authors to alleviate the context sparsity. Moreover, we can not only mine the topic distribution of each author, but also monitor the topic distribution of each time. Hence, our work can detect bursts of topic volumes from posts. Different from TAT, our work simultaneously models sentiments and topics to discover sentiment-aware topics and then detects bursts from these sentiment-aware topics.

2.2. Topic models on short texts

Recently there exists much work of topic modeling for the posts on social media. However, it suffers from the context sparsity problem of the posts. To overcome the sparsity problem, some work attempted to aggregate posts into pseudo-documents. In [11], Twitter-LDA aggregated posts from the same users into lengthy pseudo-documents, where words in the same post belong to the same topic. In [10], posts in TimeUserLDA were aggregated by timeslices or users for finding bursty topics where posts belong to two kinds of topics: personal topics and temporal topics. Similar to TimeUserLDA, posts in TUK-TTM [22] were also aggregated by timeslices or users. Moreover, TUK-TTM was utilized for time-aware personalized hashtag recommendation. These models can alleviate the problem of the context sparsity of short texts on social media. In our work, we want to jointly model sentiments and topics of posts. However, previously introduced work did not consider an extra aspect of short texts, i.e., the sentiment polarities of short texts.

2.3. Joint Sentiment/Topic Models

Recently some topic models have been extended to model topics and sentiments jointly. The first work of joint topic and sentiment modeling is Topic-Sentiment Mixture model (TSM) [23]. In TSM, a sentiment is a special kind of topic and each word is generated from either a sentiment or a topic. The relation between sentiments and topics cannot be mined by TSM. At the same time, TSM is based on PLSA and suffers from the problems of inference on new documents and overfitting the data. To overcome these shortcomings, Joint Sentiment-Topic model (JST) [8] was proposed to use a two-level sentiment-topic model based on LDA. In JST, sentiment labels are associated with documents and, in each document , topics are associated with sentiment labels and words are associated with both sentiment labels and topics. Reverse-JST (RJST) [24] is a variant of JST where the position of sentiment and topic layer is swapped. In JST, topics were generated conditioned on a sentiment polarity, while in RJST sentiments were generated conditioned on a topic. Aspect/Sentiment Unification Model (ASUM) [9] is similar to JST. In ASUM, words in the same sentence belong to the same sentiment and topic. Sentiment Topic Model with Decomposed Prior (STDP) [25] is another variant of JST. STDP first determined whether a word in a document is used as a sentiment word or an ordinary topic word, and then chose the sentiments for sentiment words. Time-aware Topic-Sentiment Model (TTS) [26] extracted the hidden topics from texts and modeled the association between topics and sentiments and tracked the strength of topic-sentiment association over time. In TTS, time is viewed as a special word to bias the topic-sentiment distributions. Different from other models, we use time to aggregate short texts and generate pseudo documents for modeling topics and sentiments. JST, RJST, ASUM, STDP and TTS are designed for normal texts where each piece of text has rich context to infer topics and sentiments. In this work, we give methods to model posts (i.e., short and informal texts) on social media, while all of these models lose efficacy in the case of short and informal texts. MaxEnt-LDA [27] jointly discovered both aspects and aspect-specific opinion words by integrating a supervised maximum entropy algorithm to separate opinion words from objective ones. However, it does not further discover aspect-aware sentiment polarities of opinion words, which can mine fine-grained sentiment information.

In our model, we focus on short and informal texts on social media. There exists some work about LDA-based sentiment analysis on social media. Twitter Opinion Topic Model (TOTM) [28] aggregated or summarized opinions of a product from posts, which can discover target specific opinion words and improve opinion prediction. Topic Sentiment Latent Dirichlet Allocation (TSLDA) [29] utilized sentiments on social media for predicting stock price movement. TSLDA distinguished the ways of modeling topic words and opinion words, i.e., topic words were drawn from the topic-word distribution and opinion words were drawn from the sentiment-topic-word distribution. Although these two work focuses on posts of social media, they do not solve the context sparsity problem of posts.

2.4. Detecting bursty topics

To detect bursts from data streams, e.g, news stream, sina weibos, we aim to aggregate information and reduce redundancy within the information flow in the data stream. To find bursty patterns in these stream, Kleinberg [18] proposed a 2-state automaton to model the arrival volume of documents in each timestamp of a stream and bursty volumes can be discovered from the underlying state sequence. Based on the method of [18], Takahashi et al. [19] and Koike et al. [30] proposed to apply Kleinberg's modeling of bursts to topics discovered by time-aware topic models, such as DTM [31] and DJST [32]. In our work, we also utilize Kleinberg's modeling of bursts from sentiment-aware topics.

Xie et al. [33,34] proposed a solution, TopicSketch, which maintains a data sketch of the accelerations of three quantities at any time stamp: (1) The whole post stream, (2) Each word in the post, (3) Each pair of words in the post. In TopicSketch, bursty topic detection task was formulated as an optimization problem of minimizing the square error between the observed value and the expectation of word acceleration. TopicSketch focuses on detecting bursty words or word-paris, where detected topics are hard to be interpreted. Yin et al. [35] also designed an optimization function to detect both bursty topics and stable topics. Yan et al. [36] proposed a probabilistic model, Bursty Biterm Topic Model(BBTM), for bursty topics which is based on Biterm Topic Model (BTM). BTM modeled a word-pair in the same post as the same topic. Based on BTM, BBTM added a variable to detect bursty topics. BBTM is based on the assumption that a word-pair in the post belongs to the same topic, which is suitable for topics. However, two words in the same post do not always express the same sentiment polarities. Hence, this approach is not flexible for detecting bursty sentiment-aware topics. Different from their work, we focus on detecting bursts from sentiment-aware topics, which can capture more fine-grained bursty topics.

3. Terminology definition

In this section, we define the basic terminologies we will use in this paper.

- **Post**: A post contains a sequence of words which express the opinions and the thoughts of people with different formats (e.g., a weibo or a review).
- **User**: Each user-generated post has a user identification that specifies who publishes the post.
- **Timeslice**: Each user-generated post has a timeslice that specifies when the user publishes the post. In this work, the length of timeslice is a day.
- **Topic**: A topic is a discrete piece of content that is about a specific subject, has an identifiable purpose (e.g., an event, a current hot problem and a product). Here, a topic is represented as a list of words.
- **Sentiment**: Sentiment is a label which refers to the polarity in which a concept or opinion is interpreted [37], i.e., "positive" and "negative". For example, "positive" is a sentiment for the post "Tom was glad to visit his friends.".
- **Sentiment-aware topic**: A sentiment-aware topic is a topic labeled with a sentiment polarity. For example, the overall sentiment of the topic "Obama's visit to cuba" is positive, hence the topic "Obama's visit to Cuba" is a positive topic [15].
- **Bursty topic**: Sina weibo, Twitter and other social media platforms are the most important and timely sources to detect and track the breaking news/events before the traditional medias pick up on and cover them. The news/event will trigger a burst of relevant posts which talk about the same topics. The burst of the posts is called "bursty topic". For example, "东方之星号客轮翻沉事件" ("Sinking of Dongfang zhi Xing"), the ship traveling on the Yangtze River in Jianli, Hubei Province with 454 people on board was capsized by a severe thunderstorm on June 1, 2015. When the event occurred, the volume of weibos sent spiked to more than 5000 per second when people post news about the situation of the rescue process [10].

4. The proposed models

In this section, we firstly introduce the notation and formally formulate our model. Then, we give the method for learning parameters. Finally, we present the method of incorporating prior knowledge into our model.

4.1. The generation process

It is assumed that there exists a stream of M posts, denoted as $d_1, d_2, \ldots, d_M$. Each post d_m is generated by a user $u(d_m)$ within a timeslice $t(d_m)$ and the post d_m contains a bag of words, denoted as $\{w(d_{m,1}), w(d_{m,2}), \ldots, w(d_{m,N(d_m)})\}$.

In LDA, a document is viewed as a multinomial distribution over topics and a topic is a multinomial distribution over words. In JST, each document is associated with the sentiment/topic distribution, i.e., each sentiment in the document has a topic distribution; the document also has a sentiment distribution for document-level sentiment-classification; a sentiment/topic is a multinomial distribution over words. LDA and JST only work well for lengthy documents, since the lengthy documents have rich contexts. Based on the analysis of posts on the social media, words in the same post tend to belong to the same topic [11]. However, the sentiment polarities of words in the same post can be different [12]. At the same time, to model the association between sentiments and topics, we also add a sentiment label for each post, which is determined by the overall sentiment of all the words in the post.

On social media, a part of posts talks about stable topics which are related to users' personal interests with certain sentiments. Thus we introduce a global sentiment/topic distribution δ for each user to capture personal long-term topical interests and sentiment preferences. Another part of posts is about temporal topics which are related to current events with the corresponding sentiments. Thus, we add a time-dependent sentiment/topic distribution θ for each timeslice to capture temporal topics and the sentiments towards the topics.

Here, we construct generative process of all the posts in the stream. When a user $u(d_m)$ publishes a post d_m within a timeslice $t(d_m)$, the user first utilizes the variable $y(d_m)$, which is drawn from the global user-timeslice switch distribution ε, to decide whether the post talks about a stable topic or a temporal topic. Then the user chooses a sentiment label $l(d_m)$ for the post from the document-sentiment $\pi(d_m)$. If the user chooses a stable topic $u(d_m)$ and a sentiment label $l(d_m)$, he then selects a topic $z(d_m)$ from $\delta_{u(d_m),l(d_m)}$; otherwise, he selects a topic $z(d_m)$ from $\theta_{t(d_m),l(d_m)}$. For each word $w(d_{m,\,i})$ in the post d_m, the user first chooses a sentiment label $l(d_{m,\,i})$. With the chosen topic $z(d_m)$ and sentiment label $l(d_{m,\,i})$, the word is drawn from the sentiment-topic word distribution $\varphi_{l(d_{m,i}),z(d_m)}$.

The notations in this paper are summarized in Table 1, which contains all the variables and parameters in our model. Fig. 3 shows the graphical representation of the generation process. Formally, the generative process for each post is as follows:

1. Draw $\varepsilon \sim Beta(\gamma)$
2. For each timeslice $t = 1, \ldots, T$
   i. For each sentiment label $s = 0, 1, 2$
      a. Draw $\theta_{t,\,s} \sim \mathrm{Dir}(\alpha)$
3. For each user $u = 1, \ldots, U$
   i. For each sentiment label $s = 0, 1, 2$
      a. Draw $\delta_{u,\,s} \sim \mathrm{Dir}(\alpha)$
4. For each sentiment label $s = 0, 1, 2$
   i. For each topic $k = 1, \ldots, K$
      a. Draw $\varphi_{s,\,k} \sim \mathrm{Dir}(\beta)$
5. For each post d_m, $m = 1, \ldots, M$
   i. Draw $\pi(d_m) \sim \mathrm{Dir}(\lambda)$

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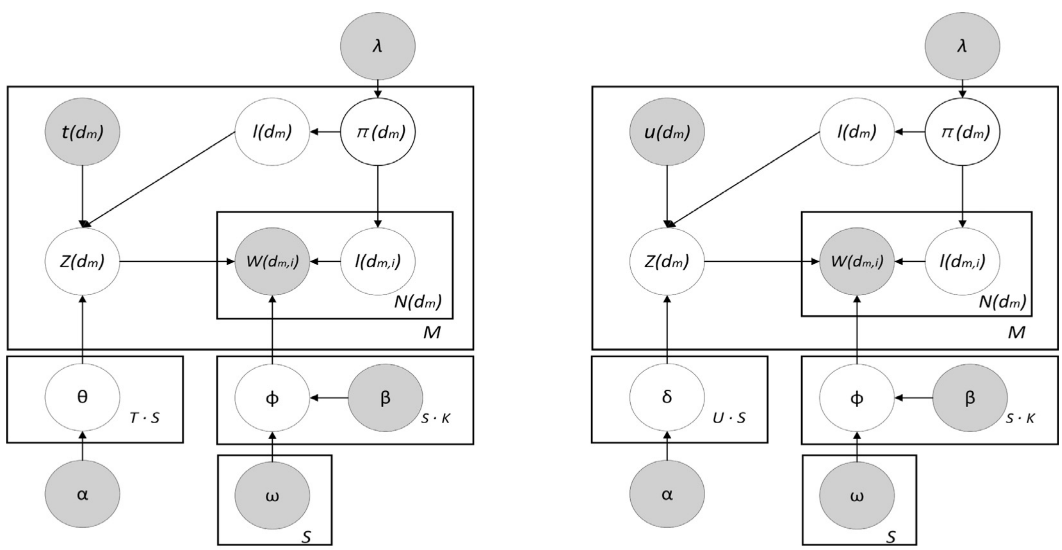
Table 1
Notations used in the TUS-LDA model.

Symbol	Description
M, K	Number of documents, topics
V, U, T	Number of vocabulary, users, timeslices
z,w,y	All the topics, words, user-timeslice switches
t, u	All the timeslices and users
$\mathbf{l}$, $\bar{\mathbf{l}}$	All the sentiments of posts and words
$N(d_m)$	Number of word tokens in post d_m
$u(d_m)$, $t(d_m)$ $y(d_m)$, $l(d_m)$	User,timeslice, user-timeslice switch and sentiment of post d_m
$z(d_m)$	Topic of post d_m
$l(d_{m,\ i})$	Sentiment of word $w(d_{m,\ i})$
ε	Beta distribution of stable topics and temporal topics
$\pi(d_m)$	Document-sentiment distribution, $\Omega = \{\pi(d_m)\}_{m=1}^{M}$
$\theta_{t,s}$	Timeslice-sentiment topic distribution, $\Theta = \{\theta_{t,s}\}_{t=1,s=1}^{T*S}$
$\delta_{u,s}$	User-sentiment topic distribution, $\Phi = \{\delta_{u,s}\}_{u=1,s=1}^{U*S}$
$\varphi_{s,k}$	Sentiment-topic word distribution, $\Psi = \{\varphi_{s,k}\}_{s=1,k=1}^{S*K}$
α	Hyper-parameters of $\theta_{t,\ s}$ and $\delta_{u,\ s}$
β, λ	Hyper-parameters of $\varphi_{s,\ k}$, π_m
γ	Hyper-parameters of ε
ω_s	Prior knowledge of $\varphi_{s,\ k}$



(a) TS-LDA (b) US-LDA

Fig. 2. The graphical representation of the proposed model (TS-LDA (a), US-LDA (b)). Shaded circles are observations or constants. Unshaded ones are hidden variables.

ii. Draw $l(d_m) \sim \text{Multi}(\pi(d_m))$
iii. Draw $y(d_m) \sim Bernoulli(\varepsilon)$
iv. if $y(d_m)$=0, Draw $z(d_m) \sim \text{Multi}(\theta_{u(d_m),l(d_m)})$ or if $y(d_m)$=1, Draw $z(d_m) \sim \text{Multi}(\delta_{t(d_m),l(d_m)})$
v. For each word w $i = 1, \ldots N(d_m)$
 a. Draw $l(d_{m,\ i}) \sim \text{Multi}(\pi(d_m))$
 b. Draw $w(d_{m,i}) \sim \text{Multi}(\varphi_{z(d_m),l(d_{m,i})})$

There are two degenerate variations of our model which are shown in the experiments. The first one is depicted in Fig. 2(a), which considers the temporal topic-sentiment distribution. The second one is depicted in Fig. 2(b), which only considers the stable topic-sentiment distribution. We refer to our complete model as TUS-LDA, the model in Fig. 2(a) as TS-LDA and the model in Fig. 2(b) as US-LDA.

4.2. Parameters inference

Similar to LDA, exact inference is intractable in our models. Hence approximate estimation approaches, such as Gibbs Sampling [38], are utilized to solve the problem. Gibbs Sampling, a special case of Markov Chain Monte Carlo (MCMC) [39], is a relatively simple algorithm of approximate inference for our models.

4.2.1. Joint distribution

The joint probability of words, users, timeslices, timeslices-user switches, topics and sentiments can be factored in Eq. (1), where ε, π, φ, δ and θ are integrated and $\vec{n_m}$ counts the number of three sentiment labels of a post and the words in the post (all the notations are illustrated in Table 1.).

$$
\begin{aligned}
&P_{TUS-LDA}(\mathbf{z}, \mathbf{w}, \mathbf{t}, \mathbf{u}, \mathbf{y}, \mathbf{l}, \bar{\mathbf{l}} | \alpha, \gamma, \lambda, \beta, \omega) \\
&= \int_{\varepsilon} P(\mathbf{y}, \varepsilon | \gamma) d\varepsilon \int_{\pi} P(\mathbf{l}, \pi | \lambda) P(\bar{\mathbf{l}}, \pi | \lambda) d\pi \int_{\delta} P(\mathbf{z}, \delta | \mathbf{y}, \mathbf{l}, \alpha) d\delta \\
&\int_{\theta} P(\mathbf{z}, \theta | \mathbf{y}, \mathbf{l}, \alpha) d\theta \int_{\varphi} P(\mathbf{w}, \varphi | \mathbf{z}, \bar{\mathbf{l}}, \beta, \omega) d\varphi \\
&= P(\mathbf{y}|\gamma) P(\mathbf{l}|\lambda) P(\mathbf{z}|\mathbf{y}, \mathbf{l}, \alpha) P(\bar{\mathbf{l}}|\lambda) P(\mathbf{w}|\mathbf{z}, \bar{\mathbf{l}}, \beta, \omega) \\
&= \frac{\Delta(\vec{n}_y + \vec{\gamma})}{\Delta(\vec{\gamma})} \times \prod_{m=1}^{M} \frac{\Delta(\vec{n}_m + \vec{\lambda})}{\Delta(\vec{\lambda})} \times \prod_{u=1}^{U} \prod_{s=1}^{S} \frac{\Delta(\vec{n}_{u,s} + \vec{\alpha})}{\Delta(\vec{\alpha})}
\end{aligned}
$$

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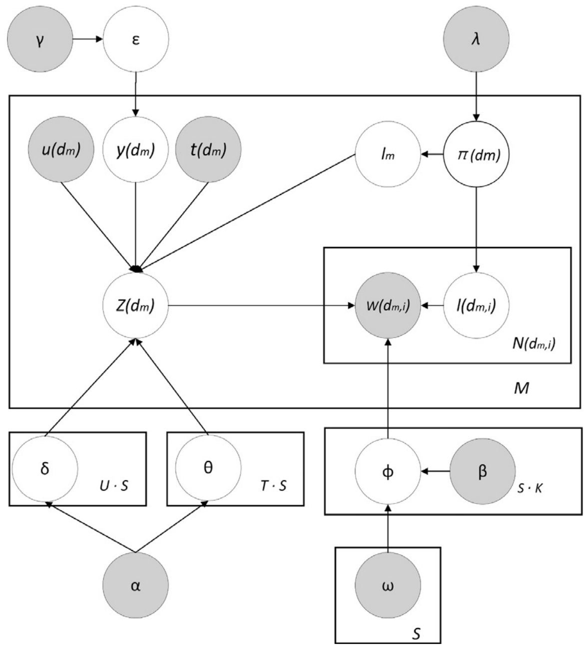

Fig. 3. The graphical representation of TUS-LDA. Shaded circles are observations or constants. Unshaded ones are hidden variables.

$$\times \prod_{t=1}^{T}\prod_{s=1}^{S}\frac{\Delta(\vec{n}_{t,s}+\vec{\alpha})}{\Delta(\vec{\alpha})} \times \prod_{s=1}^{S}\prod_{k=1}^{K}\frac{\Delta(\vec{n}_{s,k}+\vec{\beta})}{\Delta(\vec{\beta})};$$
$$\Delta = \frac{\prod_{k=1}^{dim\,\vec{x}}\Gamma(x_k)}{\Gamma(\prod_{k=1}^{dim\,\vec{x}} x_k)},\ \vec{n}_y=\{n_y^0,n_y^1\},\ \vec{n}_m=\{n_m^{pos},n_m^{neg},n_m^{neu}\}$$
$$\vec{n}_{u,s}=\{n_{u,s}^k\}_{k=1}^K,\ \vec{n}_{t,s}=\{n_{t,s}^k\}_{k=1}^K,\ \vec{n}_{s,k}=\{n_{s,k}^v\}_{v=1}^V \quad (1)$$

For the first term in Eq 1, by integrating out ε, we obtain $\frac{\Delta(\vec{n}_y+\vec{\gamma})}{\Delta(\vec{n}_{y,-i}+\vec{\gamma})}$. Thereinto, $\Delta = \frac{\prod_{k=1}^{dim\,\vec{x}}\Gamma(x_k)}{\Gamma(\prod_{k=1}^{dim\,\vec{x}} x_k)}$ describes the coefficient of dirichlet distribution where Δ is utilized for simply describing the coefficient of dirichlet distribution in Eq. (1). $\vec{n}_y$ is the numbers of posts which are assigned to switch y, i.e., n_y^0 is the number of posts assigned to user-level sentiment-topics and n_y^1 is the number of posts assigned to time-level sentiment-topics. Similarly for the second term, by integrating out π, we obtain $\frac{\Delta(\vec{n}_m+\vec{\lambda})}{\Delta(\vec{\lambda})}$, where $\vec{n}_m$ is the number of posts assigned to different kinds of sentiment polarities, i.e., $\vec{n}_m^{pos}$ represents positive posts, $\vec{n}_m^{neg}$ represents negative posts and $\vec{n}_m^{neu}$ represents neutral posts. The three terms $\frac{\Delta(\vec{n}_{u,s}+\vec{\alpha})}{\Delta(\vec{\alpha})}$ and the four terms $\frac{\Delta(\vec{n}_{t,s}+\vec{\alpha})}{\Delta(\vec{\alpha})}$ are similar. We respectively integrate out δ and θ, where $\vec{n}_{u,s}$ are the numbers of posts assigned to different topics under user u and sentiment s and $\vec{n}_{t,s}$ is the numbers of posts assigned to different topics under time t and sentiment s. The final term, by integrating out φ, we obtain $\frac{\Delta(\vec{n}_{s,k}+\vec{\beta})}{\Delta(\vec{\beta})}$, where $\vec{n}_{s,k}$ are the numbers of different words assigned to topic k and sentiment s.

4.2.2. Posterior distribution

Posterior distribution is estimated as follows: for the i-th post, the user u_i and timeslice t_i are known. y_i, z_i and l_i can be jointly sampled given all other variables. Here, we use $\mathbf{y}$ to denote all the hidden variables y and $\mathbf{y}_{-i}$ to denote all the other y except y_i. All the hyperparameters (as shown in Table 1) are omitted.

$$P(y_i=0, z_i=k, l_i=s|\mathbf{y}_{-i}, \mathbf{z}_{-i}, \mathbf{l}_{-i}, \bar{\mathbf{l}}, \mathbf{w})$$
$$= \frac{P(\mathbf{y},\mathbf{z},\bar{\mathbf{l}},\mathbf{l},\mathbf{w})}{P(\mathbf{y}_i,\mathbf{z}_i,\bar{\mathbf{l}}_i,\mathbf{l}_i,\mathbf{w}_i)} = \frac{P(\mathbf{y})}{P(\mathbf{y}_i)}\frac{P(\mathbf{l})}{P(\mathbf{l}_i)}\frac{P(\mathbf{z}|\mathbf{y},\mathbf{l})}{P(\mathbf{z}_i|\mathbf{y}_i,\mathbf{l}_i)}\frac{P(\mathbf{w}|\mathbf{z},\mathbf{l})}{P(\mathbf{w}_i|\mathbf{z}_i,\mathbf{l}_i)}$$
$$\propto \frac{\Delta(\vec{n}_y+\vec{\gamma})}{\Delta(\vec{n}_{y,-i}+\vec{\gamma})} \times \frac{\Delta(\vec{n}_d+\vec{\lambda})}{\Delta(\vec{n}_{d,-i}+\vec{\lambda})} \times \frac{\Delta(\vec{n}_{u,s}+\vec{\alpha})}{\Delta(\vec{n}_{u,s,-i}+\vec{\alpha})}$$
$$\times \frac{\Delta(\vec{n}_{s,k}+\vec{\beta})}{\Delta(\vec{n}_{s,k,-i}+\vec{\beta})} \propto \frac{\gamma_0+n_{y,-i}^0}{\sum_{p=1}^2\gamma_p+n_{y,-i}^p} \times \frac{\lambda_s+n_{m,-i}^s}{\sum_{s'=1}^S\lambda_{s'}+n_{m,-i}^s}$$
$$\times \frac{\alpha_k+n_{u,s,-i}^k}{\sum_{k=1}^K\alpha_{k'}+n_{u,s,-i}^{k'}} \times \frac{\prod_{v=1}^V\prod_{n_v=0}^{N_{(v)}-1}(\beta_{s,k}+n_{s,k,-i}^v+n_v)}{\prod_{n=0}^{N-1}(\sum_{v'=1}^V(\beta_{s,k}+n_{s,k,-i}^{v'})+n)} \quad (2)$$

If y_i=0, the i-th post talks about a stable topic, the sampling procedure is formulated as shown in Eq. (2); otherwise, the i-th post talks about a temporal topic, the sampling procedure is formulated as shown in Eq. (3).

$$P(y_i=1, z_i=k, l_i=s|\mathbf{y}_{-i}, \mathbf{z}_{-i}, \mathbf{l}_{-i}, \bar{\mathbf{l}}, \mathbf{w})$$
$$\propto \frac{\gamma_1+n_{y,-i}^1}{\sum_{p=1}^2\gamma_p+n_{y,-i}^p} \times \frac{\lambda_s+n_{m,-i}^s}{\sum_{s'=1}^S\lambda_{s'}+n_{m,-i}^s} \times \frac{\alpha_k+n_{t,s,-i}^k}{\sum_{k'=1}^K\alpha_{k'}+n_{t,s,-i}^{k'}}$$
$$\times \frac{\prod_{v=1}^V\prod_{n_v=0}^{N_{(v)}-1}(\beta_{s,k}+n_{s,k,-i}^v+n_v)}{\prod_{n=0}^{N-1}(\sum_{v'=1}^V(\beta_{s,k}+n_{s,k,-i}^{v'})+n)} \quad (3)$$

For the j-th word in the i-th post, the sampling procedure is shown in Eq. (4).

$$P(\bar{l}_{ij}=s|\mathbf{z}, \bar{\mathbf{l}}_{-ij}, \mathbf{w}, \mathbf{y}, \mathbf{l}) = \frac{P(\mathbf{z},\bar{\mathbf{l}},\mathbf{w})}{P(\mathbf{z}_{i,j},\bar{\mathbf{l}}_{i,j},\mathbf{w})} \propto \frac{P(\bar{\mathbf{l}})}{P(\bar{\mathbf{l}}_{i,j})} \times \frac{P(\mathbf{w}|\mathbf{z},\bar{\mathbf{l}})}{P(\mathbf{w}_{i,j}|\mathbf{z}_i,\bar{\mathbf{l}}_{i,j})}$$
$$\propto \frac{\Delta(\vec{n}_d+\vec{\lambda})}{\Delta(\vec{n}_{d,-\{i,j\}}+\vec{\lambda})} \times \frac{\Delta(\vec{n}_{s,k}+\vec{\beta})}{\Delta(\vec{n}_{s,k,-\{i,j\}}+\vec{\beta})}$$
$$\propto \frac{\lambda_s+n_{m,-ij}^s}{\sum_{s'=1}^S(\lambda_{s'}+n_{m,-ij}^{s'})} \times \frac{\beta_{s,k}^v+n_{s,k.-ij}^v}{\sum_{v'=1}^V(\beta_{s,k}^{v'}+n_{s,k.-ij}^{v'})} \quad (4)$$

These posterior distributions, i.e., π, δ, θ and ϕ, all obey dirichlet distribution, where the expectation of dirichlet distribution $Dir(x|\alpha)$ (x and α are K-dimension vectors) can be computed as $E(x_i)=\frac{\alpha_i}{\sum_k\alpha_k}$.[2] Samples obtained from MCMC are then utilized for estimating the distributions π, δ and θ, ϕ, i.e., computing the expectation of π (Eq. (5)), δ (Eq. (6)), θ (Eq. (7)), ϕ (Eq. (8)).

$$\pi_m^s = \frac{\lambda_s+n_m^s}{\sum_{s'=1}^S(\lambda'_s+n_m^{s'})} \quad (5)$$

$$\delta_{u,s}^k = \frac{\alpha_k+n_{u,s}^k}{\sum_{k'=1}^K(\alpha_{k'}+n_{u,s}^{k'})} \quad (6)$$

$$\theta_{t,s}^k = \frac{\alpha_k+n_{t,s}^k}{\sum_{k'=1}^K(\alpha_{k'}+n_{t,s}^{k'})} \quad (7)$$

$$\varphi_{s,k}^v = \frac{\beta_{s,k}^v+n_{s,k}^v}{\sum_{v'=1}^V(\beta_{s,k}^{v'}+n_{s,k}^{v'})} \quad (8)$$

4.2.3. Gibbs sampling algorithm

A complete overview of Gibbs sampling procedure is given in Algorithm 1 (all the notations are listed in Table 1).

[2] https://en.wikipedia.org/wiki/Dirichlet_distribution.

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Algorithm 1: Inference on TUS-LDA.

```
Input: α, γ, λ, β, ω
Initialize matrices Ω, Θ, Φ, Ψ and ε.
for iteration c=1 to numIterations do
    for post m=1 to M do
        Exclude post m and update count variables.
        Sample a timeslice-user switch, topic and sentiment
        label for post m.
        if y=0 then
            Use Eq 2
        if y=1 then
            Use Eq 3
        Update count variables with new timeslice-user
        switch, topic and sentiment label.
        for n=1 to n_m do
            Exclude word w_n and update count variables.
            Sample the sentiment label for word w_n using Eq 4.
            Update count variables with new sentiment label.
Update matrices Ω, Φ, Θ, Ψ using Eq 5, 6, 7, 8
```

4.3. Incorporating prior knowledge

Drawing on the experience of JST and RJST [24], we also add an additional dependency link of φ on the matrix ω of size $S*V$, which is utilized for encoding word prior sentiment information into TUS-LDA and its variants. To incorporate prior knowledge into TUS-LDA and its variants, we first set all the values of ω to 1. Then the matrix ω is updated with a sentiment lexicon which contains words with the corresponding sentiment labels, i.e., "positive" and "negative". For each term $w \in \{1, \ldots, V\}$ in the corpus, if w is found in the sentiment lexicon with the sentiment label $l \in \{1, \ldots, S\}$, the element ω_{lw} is set as 1 and other elements of the word w are set as 0. The element ω_{lw} is updated as follows:

$$\omega_{lw} = \begin{cases} 1 & \text{if S(w)=l} \\ 0 & \text{otherwise} \end{cases}$$

The Dirichlet prior β of the size $S*K*V$ are multiplied by the matrix ω (a transformation matrix) to capture the word prior sentiment polarity.

4.4. Burst detection from sentiment-aware topics

Kleinberg [18] proposed a framework that models burst. The framework contains two types of modeling bursts [19]. The first one considers the arrival time of relevant posts, where a sequence of posts is regarded as bursty if their inter-arrival gaps are smaller than usual (for example, 5% smaller than usual). The second one is based on the volumes of relevant posts arriving in discrete batches, where a sequence of batched arrivals could be considered as bursty when the volume of relevant posts in the batch is obviously larger than other batches. Based on the characteristic of our model, we choose the second type to model bursts in sentiment-aware topics.

We suppose that there exist T days of posts; after jointly sentiment and topic modeling, the t-th day B_t in the posts $\mathbf{B} = (B_1, \ldots, B_T)$ of T days contains n_t^{sk} posts, with sentiment s and topic k, out of a total of n_t. Let $R = \sum_{t=1}^{T} n_t^{sk}$ and $N = \sum_{t=1}^{T} n_t$. A 2-state automaton A^2 is defined for each sentiment-aware topic where the state q_0 denotes the non-burst state, and the state q_1 denotes the burst state. For each q_i of two states q_0 and q_1, there is an excepted fraction p_i of each sentiment-aware topic. Set $p_0 = \frac{R}{N}$, and $p_1 = p_0 \varsigma$, where $\varsigma > 1$ is a scaling parameter, and $p_1 \leq 1$ holds for p_1. In this paper, we empirically set ς as 2.

Viewed in a generative fashion, state q_i produces a mixture of posts with sentiment s and topic k and posts with other sentiment-aware topics according to a binomial distribution with probability p_i. The cost of a state sequence $\mathbf{q} = (q_{i_1}, \ldots, q_{i_T})$ in A^2 is defined as follows. If the automaton is in state q_i when the t-th batch of posts arrives, the cost can be derived by Eq. (9), since this is the negative logarithm of the probability that n_t^{sk} posts would be generated using a binomial distribution with probability p_i.

$$\sigma(i, n_t, n_t^{sk}) = -ln[\binom{n_t}{n_t^{sk}} p_i^{n_t^{sk}} (1 - p_i)^{n_t - n_t^{sk}}] \tag{9}$$

There is also a cost of $\tau(i_t, i_{t+1})$ associated with the state transition from q_{i_t} to $q_{i_{t+1}}$. $\tau(i_t, i_{t+1})$ is defined so that the cost of moving from the non-burst state to the burst state is non-zero, but there is no cost for the automaton to end a burst and drop down to a non-burst. Specifically, when $j > i$, moving from q_i to q_j incurs a cost of $(j - i)\gamma$, where $\gamma > 0$ is a parameter; when $j \leq i$, the cost is 0. In this paper, we set γ as 1. The cost of the state transition is shown as follow:

$$\tau_{i,j} = \begin{cases} (j - i)\gamma & \text{j>i} \\ 0 & \text{j≤i} \end{cases}$$

Then, given a sequence of posts $\mathbf{B} = (B_1, \ldots, B_T)$, the goal is to find a state sequence $\mathbf{q} = (q_{i_1}, \ldots, q_{i_T})$ that minimizes the cost function in Eq. (10):

$$c(\mathbf{q}|\mathbf{B}) = \left(\sum_{t=0}^{T} \tau(i_t, i_{t+1}) \right) + \left(\sum_{t=1}^{T} \sigma(i_t, n_t, n_t^{sk}) \right) \tag{10}$$

We can use dynamic programming to detect the latent state sequence for each sentiment-aware topic. Finally, in each sentiment-aware topic, a burst is marked by a continuous subsequence of burst states.

4.5. Weight of a sentiment-aware topic's burst

Given an optimal state sequence, bursts of positive intensity correspond to intervals in which the state is q_1 rather than q_0. For such a burst $[t_k, t_l]$, we can define the *weight* of the burst as shown in Eq. (11):

$$bw(t_k, t_l) = \sum_{t=t_k}^{t_l} (\sigma(0, n_t, n_t^{sk}) - \sigma(1, n_t, n_t^{sk})) \tag{11}$$

In other words, the weight is equal to the improvement in cost incurred by state q_1 over the interval rather than state q_0. Observe that in an optimal sequence, the weight of every burst is non-negative. Intuitively, bursts of larger weight correspond to more prominent periods of elevated activity.

5. Experiments

5.1. Dataset description and preprocessing

For experiments, we performed sentiment classification (quantitative analysis) and burst detection in sentiment-aware topics (quality analysis) on Chinese sina weibo[3], which are characterized by their 140 characters text. We selected a weibo data set to evaluate our models. The original data set is extracted from 1st June, 2015 to 30th June, 2015 (30 days in total). Each weibo contains the content, the release timeslice and the user information.

To reduce low-quality weibos, we performed the following normalization steps (1) utilizing "Jieba"[4] for Chinese word segmenta-

[3] http://weibo.com/.

[4] "Jieba" (Chinese for "to stutter") Chinese text segmentation: built to be the best Python Chinese word segmentation module. GitHub: https://github.com/fxsjy/jieba/.

tion, which is the basis of Chinese information processing. (2) removing non-Chinese words and stop words. (3) removing words with document frequency less than 5, since topic models only can work well when topic words have frequent co-occurrence patterns. (4) filtering out the weibos with length less than 2. (5) removing duplicate weibos. At last, we left 190,352 valid weibos, 227,386 words and 5514 users. Due to the lack of sentiment labels on the weibos, we randomly selected and annotated weibos. Finally, we left 100 positive weibos and 100 negative weibos for sentiment classification evaluation.

We compared TUS-LDA with four joint sentiment and topic models in sentiment classification on this short texts collection: (a) Joint sentiment and topic model (JST), which takes each weibo as a document; (b) Aspect and Sentiment Unification Model (ASUM), which makes each weibo belong to the same sentiment and topic; (c) TS-LDA, a simplified version of TUS-LDA, which only aggregates weibos in the same timesclie; (d) US-LDA, another simplified version of TUS-LDA, which only aggregates weibos in the same user. All the five models belong to weakly-supervised model without labeled samples. Moreover, in sentiment classification, we also compared TUS-LDA with lexicon-based approach [40], a weakly supervised method without labeled samples, and SVM-based approach [41], a supervised algorithm with labeled samples. In burst detection, we compared TUS-LDA with Dynamic joint sentiment and topic model (DJST) and TS-LDA.

5.2. Sentiment lexicon

In JST [8] and our models, each sentiment label is viewed as a special kind of topic that we have known in advance. To improve the accuracy of sentiment detection, we need to incorporate prior knowledge or subjectivity lexicon (i.e., words with positive or negative polarity). Here, we chose NTUSD[5], a chinese sentiment lexicon with 11,086 words, which consists of a set of positive and negative words, e.g., "高兴" ("happy"): positive and "伤心" ("sad"): negative. It defines the positive and negative semantic orientation of words.

5.3. Parameter settings

To optimize the number of topics K, we empirically ran the models with four values of K: 20, 40, 60, 80, 100 based on the scale of training corpus. In our model, we simply selected symmetric Dirichlet prior vectors as is empirically done in JST and ASUM. For JST and ASUM, $\alpha = \frac{50}{K}, \beta = 0.01$ and $\gamma = 0.01$. For TUS-LDA, we set $\alpha = \frac{50}{K}, \gamma = 0.01, \lambda = 0.01$ and $\beta = 0.01$. These LDA-based models are not sensitive to the hyper-parameters [42]. In all the methods, Gibbs sampling was run for 1000 iterations with 200 burn-in periods.

To evaluate the effectiveness of our model, we performed both quantitative and qualitative evaluation. As we have explained in Section 4, each model gives us time series data for a number of topics. Then, by utilizing a 2-state automaton, we can obtain a set of bursty sentiment-aware topics.

5.4. Quantitative evaluation

5.4.1. Sentiment classification

In this section, we performed a sentiment classification task to predict the sentiment labels of the test data. As well as TOTM [28], our evaluations is a binary classification task, as such, the annotated weibos do not contain neutral weibos. We determined the polarity of a weibo m by selecting the polarity s based on the probability of π_m^s (π_m is the sentiment distribution of the m-th post). The function is shown in Eq. (12). Since neutral posts are excluded, each post sentiment polarity is either positive or negative. For the m-th post, if $\pi_m^{pos} > \pi_m^{neg}$, the post is decided as positive; if $\pi_m^{pos} < \pi_m^{neg}$, the post is decided as negative.

$$polarity(m) = \underset{s=\{neg,pos\}}{\operatorname{argmax}} \pi_m^s \quad (12)$$

We present the results of sentiment classification with *Accuracy*, which is the proportion of true results (both true positives and true negatives) among the total number of cases examined in the binary classification.

Table 2
Accuracy of document-level sentiment classification.

K	20	40	60	80	100
Lexicon	61.7	61.7	61.7	61.7	61.7
SVM	78.9	78.9	78.9	78.9	78.9
JST	60.7	61.8	63.5	63.8	62.4
ASUM	64.2	65.1	66.7	66.9	65.7
TS-LDA	67.4	66.5	68.7	69.1	68.2
US-LDA	66.1	66.8	68.1	67.9	66.7
TUS-LDA	69.1	69.9	70.2	69.7	68.8

Table 3
Evaluation results: Detecting bursty sentiment-aware topics (Precision, Recall, F1 are percentages(%)).

Model	Precision	Recall	F1
DJST	74.3	33.7	46.3
TS-LDA	77.6	**34.5**	**47.7**
TUS-LDA	**86.3**	31.8	46.5

Based on results of sentiment classification in Table 2, SVM-based approach performed better than all the weakly-supervised methods, since SVM-based approach is trained on labeled posts in a supervised way. However, in practical applications, it is very expensive and time-consuming to annotate enough posts. Moreover, sentiment patterns of posts change rapidly with the emergence of new topics on social media, so that supervised model will lose efficacy rapidly based on the past annotated posts [41]. In other words, supervised methods with labeled posts are only effective for the posts which are in the similar domains of annotated posts, since posts in the similar domains will share similar sentiment patterns [43]. Hence, we mainly focus on weakly-supervised methods. Moreover, supervised method cannot mine the topics hidden in the posts and discover the latent association between sentiments and topics. Based on the results of sentiment classification with all the weakly-supervised methods, we can see that TUS-LDA outperforms JST, ASUM, TS-LDA, US-LDA and Lexicon-based approach in Table 2. Specifically, the experimental results show the comparison between these models in terms of the accuracy of document-level sentiment classification. As we can see, our model outperforms all other models. TUS-LDA performed best and TS-LDA performed better than US-LDA except $K = 40$. There exist 30 timeslices and 5514 users. The number of users is far more than that of timeslices. This causes that modeling weibos aggregated in timeslices performed better than weibos aggregated in users. Aggregating weibos in timeslices or users (i.e., TUS-LDA) with $K = 60$ performed best in Chinese sina weibo. In our model, without any labeled posts, we can still achieve the best accuracy 70.2%.

5.4.2. Detection of bursty sentiment-aware topics

To evaluate the results of detecting bursts in sentiment-aware topics during the period from June 1st to June 30th, 2015, we asked two volunteers to annotate the detected bursty sentiment-aware topics. Table 3 shows the number of detected bursts, the correctly detected bursts as well as the precision of TS-LDA and

[5] http://www.datatang.com/data/44317.

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Table 4
5 bursty topics detected by TUS-LDA. The corresponding events are manually labeled.

Burst Period	Sentiment	Representative words	Corresponding Events
5th, June, 2015 -6th, June, 2015;10th, June, 2015–12th, June, 2015	Neutral	昂山素季(Aung San Suu Kyi) 访华(Visit China) 缅甸(Burma) 全国(Nationwide) 民主联盟(Democratic Alliance) 代表团(Delegation) 习近平(Jinping Xi) 率领(Lead) 会见(Meet) 主席(President)	昂山素季访华 (Aung San Suu Kyi's visit to China)
11th, June, 2015 -14th, June, 2015	Negative	儿童(Child) 孩子(Kid) 死亡(Death) 农药(Pesticide) 吃(Eat) 留守(Left-behind) 贵州(Guizhou) 中毒(Poisoning) 毕节(Bijie) 父母(Parents)	2015 年贵州毕节儿童死亡事件 ('Left-behind Children' Death in Bijie, Guizhou)
2th, June, 2015 -4th, June, 2015	Negative	东方星(Dongfangxing) 长江(Yangtze River) 客船(Passenger Ship) 沉船(Shipwrecks) 遇难者(Victims) 客轮(Passenger Ship) 翻沉 (Sinking) 遗体(Remains) 遇难(Murdered) 搜救(Rescue)	东方之星号客轮翻沉事件 (Sinking of Dongfang Zhi Xing)
6th, June, 2015 -10th, June, 2015	Positive	高考(Gaokao) 考生(Examinee) 分(Score) 高考作文(Gaokao Essay) 作文(Essay) 考试(Examination) 今年(Toyear) 加油(Cheer) 语文(Chinese) 作文题(Essay Question)	2015 年高考 (The Gaokao in 2015)
3th, June, 2015 -6th, June, 2015	Positive	中国(China) 云计算(Cloud Computing) 云(Cloud) 大会(Conference) 技术(Technology) 互联网(Internet) 创新(Innovation) 企业(Enterprise) 发展(Development) 大数据(Big Data)	第七届中国云计算大会 (The 7th China Cloud omputing Conference)

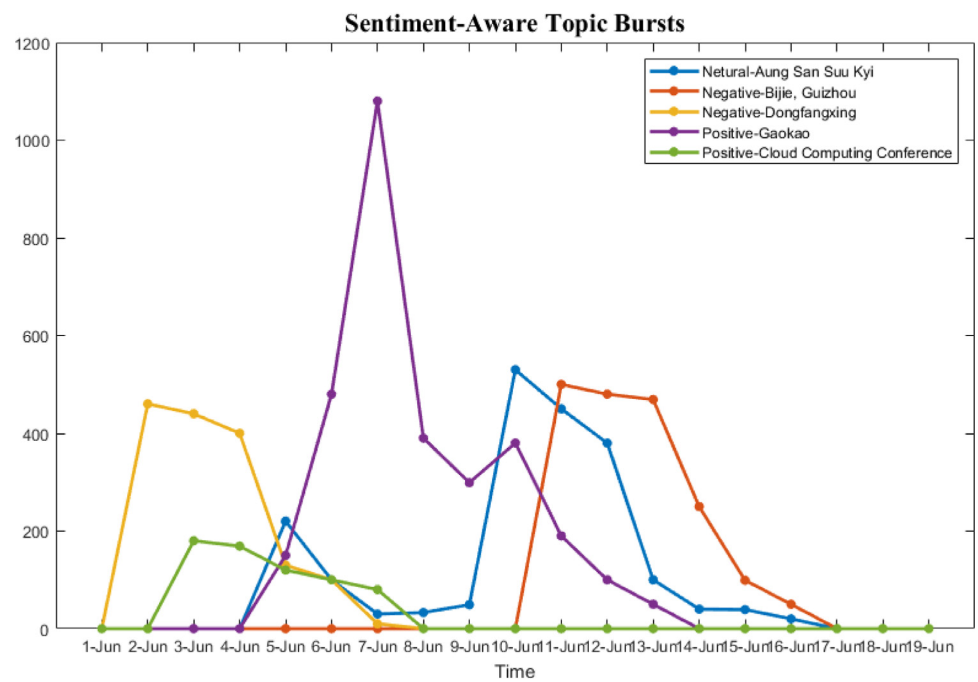

Fig. 4. Number of example sentiment-aware topics vary over time.

TUS-LDA corresponding to detected bursts. Only TS-LDA and TUS-LDA can monitor the variations of sentiment-aware topics over time, i.e., only the two models can detect bursty sentiment-aware topics. Although JST is not modeled over time, Dynamic-JST (DJST) [32] can model the variation of sentiment-aware topic over time. For TS-LDA, DJST and TUS-LDA, we can use the same burst detection method to find bursty sentiment-aware topics. According to Table 3, TUS-LDA performed worse than DJST and TS-LDA, and TS-LDA performs best. Moreover, TS-LDA performed slightly better than TUS-LDA in F1, as shown in Table 3. TUS-LDA performed best in Precision in Table 3. Since LDA-based models mine topics based on the high-frequency co-occurrence patterns, these model did well in mining high-frequency, widely discussed topics. It's non-trivial to accurately annotate all the topics hidden in the posts, so it is difficult to accurately compute the recall of burst detection in sentiment-aware topics. Hence, these manually annotated topics from posts contain sentiment-aware topics with different frequencies of occurrences, where some are high and others are relatively low. Based on our manual analysis of the results, we discover that our model performed well in mining high-frequency sentiment-aware topics which attracted the most online attention, but performed worse in the low-frequency sentiment-aware topics. Since the high-frequency sentiment-aware topics correspond to multiple sentiment-aware topics discovered by topic models, but the low-frequency ones cannot be discovered by topic models, all the LDA-based models achieved the relatively low recalls. In fact, our work mainly focused on mining the high-frequency sentiment-aware topics which draw wide attention and discussion.

5.5. Qualitative analysis

To investigate the quality of burst detection in sentiment-aware topics discovered by TUS-LDA, we listed the top-5 (ranked by weights of bursts) bursty sentiment-aware topics for visualization.

5.5.1. Examples of bursts in sentiment-aware topics

Sina weibo is the most important and timely platform from which Chinese people find out and track the breaking news and post their viewpoints about these news. Our model is to find these real events and track the burst periods of these events, by analyzing a surge of a large number of relevant weibos which belong to the same sentiment-aware topics. Then we analyze five sampled topics in Table 4. At the same time, the variation of intensity over time of the five example sentiment-aware topics is given in

Fig. 4. In Fig. 4, we can find the volume of each sentiment-aware topic varies with the occurrence, burst and fade of the corresponding event over time. Thus Fig. 4 shows that our model can indeed monitor the development of real-world events. The first bursty neutral topic #1 is "Aung San Suu Kyi's Visit to China", which contains two bursty periods, 5th June–6th June and 10th June–12th June. By the validation of volunteers, the first period is that China government publishes the news, Aung San Suu Kyi will visit China in 10th June, in 5th June. The second one is that Aung San Suu Kyi start her official visit to China. Then, two negative topics are "Left-behind Children's Death in Bijie, Guizhou" (#2) and "Sinking of Dong Fang Zhi Xing" (#3) which respectively happened in 2th June and 11th June. Finally, two positive topics are "The Gaokao in 2015" (#4) and "The 7th China Cloud Computing Conference" (#5). According to Fig. 4, the sentiment-aware topics #1, #4 and #5 are talked before their occurrences. Topic #1 corresponds to a pre-planed topic, so people can know the topic in advance. Similarly, the topics also correspond to pre-planed events and they are also periodic, i.e., "Gaokao" and "China Cloud Computing Conference" will happen per year, so these topics are also talked before they really occur. However, the negative topics #2 and #3 both correspond to accidents, which cannot be predicted in advance.

6. Conclusion and future work

In this paper, we studied the problem of detecting bursty sentiment-aware topics from the user-generated posts on the social media. Firstly, we attempted to use joint sentiment/topic models to mine sentiment-aware topics. However, the existing work of sentiment/topic models is not suitable for mining sentiment-aware topics from these short posts. Motivated by the problems, we proposed a new sentiment/topic model (TUS-LDA) that introduced the time, user information of posts to jointly model topics and sentiments. TUS-LDA can solve the context sparsity problem during modeling topics and sentiments of these posts. Moreover, we designed approaches for detecting bursts in sentiment-aware topics discovered by TUS-LDA. We compared our model with Lexicon-based approach, SVM, JST, ASUM as well as two degenerate variations of our model (TS-LDA and US-LDA) in the task of sentiment classification on sina weibo datasets. Meanwhile, we compared with DJST and TS-LDA in the task of burst detection on sentiment-aware topics. Our quantitative evaluation showed that our model outperformed other models both in sentiment classification and burst detection. Moreover, we used five examples to visualize bursty sentiment-aware topics. Since our model is weak in sentiment classification, we consider to introduce a supervised classifier to guide the modeling of sentiment, i.e., change our model to a semi-supervised sentiment topic model, in the future work. Moreover, we can also introduce uncertainty analysis for detecting bursty sentiment-aware topics on social media [44].

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