Examining the Performance of Topic Modeling Techniques in Twitter Trends Extraction

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***Abstract*—It is very important to extract the Twitter trends since it reflects the personal view over 645 million of its users. We examine the effectiveness of two topic modeling techniques i.e., standard Latent Dirichlet Allocation (LDA) and semantic-based Joint Multi-grain Topic-Sentiment (JMTS) in Twitter trends extraction. In addition, we also examine the frequent phrase method. Our finding reveals that JMTS significantly outperforms frequent phrase method and LDA by 54% and 24%, respectively.**

I. Introduction

Topic modeling is an area of research which has been born from the need to summarize and find the hidden topics of large collection of text document. Many of the topic discovery techniques are developed with conventional text corpora in mind. Web 2.0 brings other forms of large digital text corpora that eventually opens new challenges to elevate the topic modeling techniques.

One of the features of Web 2.0 is enabling user-generated content, such as microblogging. The most popular microblogging service is provided by Twitter, with more than 645 million active registered users. Even though Twitter sees famous persons like celebrities, politicians, athletes, best-seller writers and news channels as its top users (i.e. most followed users), majority of Twitter users are ordinary people. Twitter users post what they see, feel, and think about what happens in the real world. Therefore, the posts on Twitter reflect events happening in real world and making it one of the most interesting text corpora. Extracting the trends gives us understanding on what topics or events that people find most interesting.

Twitter trends are the topics most discussed by Twitter users. Hence, discovering the topics will play a great role in extracting trends from Twitter corpus. Frequency-based method, i.e. frequent phrase, is an example of naïve approach of finding trends. This technique assumes that the most frequently appearing phrases in the collection are the trends. The application of frequency-based techniques in detecting Twitter trends can be seen in [1], [2] and [3]. Probabilistic topic modeling is a sophisticated approach for trends extraction. A well-known Bayesian probabilistic topic modeling is Latent Dirichlet Allocation (LDA) [4]. LDA assumes that documents are represented as mixtures of latent topics, where each topic is characterized by distribution over words. However, LDA lacks the ability to extract semantic-based topics, and it is mainly designed for large text document. Therefore, we conduct experiment using one of the available semantic-based topic modelings, the Joint Multi-grain Topic-Sentiment (JMTS) [5]. It can discover topics from text corpus and capture sentiment aspect of topics. However, in this paper we only focus on the topic discovering ability of JMTS and examine its performance in extracting Twitter trends.

The contributions of this paper are as follows:

1) We examine Twitter trends extraction using one of semantic-based topic modelings, JMTS. To the best of our knowledge, semantic-based topic modeling extraction has not been explored before, and our work is the first attempt. Previous works in Twitter trends extraction are either using frequency-based methods or variation of LDA.
2) We perform extensive experiment on Twitter trends extraction using three different techniques over two types of dataset, general and filtered dataset. We characterize the difference in general and filtered dataset in which general dataset has a lot of conversational noises that degrades the performance of trend extraction.
3) We show that JMTS performs better in Twitter trends extraction. In particular, JMTS significantly outperforms frequent phrase method by 54% and LDA by 24% in the filtered dataset.

The remainder of the paper is organized as follows. Section II describes the related works. Section III presents the trend extracting methods to be evaluated in our experiment, which are the frequent phrase, LDA and JMTS. Section IV describes experiment procedures, which include the description of dataset and performance metrics. Section V discusses experimental result. Finally, we conclude the paper in Section VI.

II. Related Work

In the work by Lee et al. [1], the top frequent terms are extracted by calculating their tf-idf (term frequency-inverse document frequency) weights. Naaman et al. [2] detect individual terms which receive increased number of appearance as trends in their dataset. Mathioudakis et al. [3] detect bursty keywords and then perform grouping algorithm so that bursty keywords which belong to the same group will be

TABLE I
DATASET PROFILE

Dataset Name		Date Collected	# of tweets	Size (MB)
General	Day 1	2013.10.19	1,132,440	57.6
	Day 2	2013.10.20	1,247,389	61.7
	Day 3	2013.10.21	1,383,553	68.1
	Day 4	2013.10.22	979,077	48.8
	Day 5	2013.10.23	1,308,613	66.6
	Day 6	2013.10.24	1,303,091	66.4
	Day 7	2013.10.25	1,269,192	65.0
Filtered	Day 1	2013.10.24	402,340	31.4
	Day 2	2013.10.25	361,724	28.7
	Day 3	2013.10.26	343,724	27.4
	Day 4	2013.10.27	339,765	27.1
	Day 5	2013.10.28	352,360	28.1
	Day 6	2013.10.29	373,947	29.6
	Day 7	2013.10.30	393,731	31.1

recognized as the same trending topic. All these three works are frequency-based trend detection. This becomes the basis for us for including the frequent phrase as one of the trend extracting methods in our experiments.

Lau et al. [6] modify the LDA by introducing the concept of time slices, may it be an hour, a day, or a year, and documents are partitioned into this time slices. They add contribution factor parameter to enable their modified LDA to have a set of constantly evolving topics. Song et al. [7] utilize Dirichlet-multinomial regression (DMR) for extracting Twitter trends. DMR is an extension of LDA which allows conditioning on arbitrary document features by including a long-linear prior on document-topic distributions. The above approaches are based on variations LDA prior which changes unsupervised characteristic of LDA. Therefore, we consider it to be sufficed to use the basic LDA as comparison against the semantic-based JMTS.

III. Trend Extracting Methods

In this section, we describe about the methods we use in this experiment, which are the frequent phrase, LDA and JMTS.

A. Frequent Phrase

N-gram is commonly used for frequent phrase method. Unigrams (*n=1*) are unique words that appear in the document. Bigrams (*n=2*) are patterns of two-word sequence that appear together in a document. Higher order of *n* means the *n* number of words in the sequence pattern to be examined.

Presenting the keywords in unigram to human user has higher level of ambiguity, because in most languages, one word may have several different meaning. For example, a unigram ‘cell’ may lead human user to ambiguity between biological cell, prison cell, battery cell, or cell phone. However, a bigram ‘cell phone’ has certain meaning of communication domain.

In our preliminary experiment, we examined the performance of bigram, trigram (*n=3*), and quadgram (*n=4*) for extracting Twitter trends. We found out that bigram outperformed

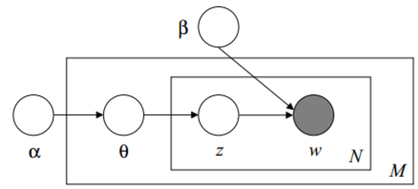

Fig. 1. Graphical Representation of LDA Generative Process.

both trigram and quadgram. This also justifies our decision to choose bigram to represent the frequent phrase techniques over other forms of n-gram.

B. LDA

LDA is a generative probabilistic model for collections of discrete data such as text corpora [4]. The basic idea of LDA is that documents are represented as random mixtures over latent topics, where each topic is characterized by distribution over words.

Fig. 1 shows the graphical representative of LDA generative process. For each document *N* in the collection, LDA generates the words in a two-stage process:

1) Randomly choose a distribution over topics θ.
2) For each word *w* in the document:
    a) Randomly choose a topic z from the distribution over topics θ in step #1.
    b) Randomly choose a word *w* from the corresponding distribution over the vocabulary.

C. JMTS

JMTS provides an unsupervised method to extract semantic aspects [5]. JMTS considers two types of multi-grain topics, which are global and local topics. Global topics represent the distinguishing properties of an object. Local topics represent the terms frequently used in discussing the global topics. Global topics are generated based on document level context and local topics are generated based on sliding window context over the corpus. JMTS uses sliding windows concept that each sliding windows cover several adjacent sentences within it. These overlapping windows allow us to use a larger co-occurrence domain. Thus, it automatically detects the frequently used terms (local topics).

Fig. 2 shows the graphical representative of JMTS generative process. The generative process is as follows:

1)
    a) For every pair of sentiment l and global topic z, draw a word distribution $\varphi^{gl}_{z,l} \sim Dir\left(\beta^{gl}\right)$; noting that $Dir\left(\beta^{gl}\right)$ is a distinct Dirichlet distribution with the Dirichlet prior in the global topic sentiment-word distribution, β^{gl}.
    b) For every pair of sentiment *l* and local topic *z*, draw a word distribution $\varphi^{loc}_{z,l} \sim Dir\left(\beta^{loc}\right)$.
2) For each document *d*,
    a) choose a sentiment distribution $\xi^{gl}_{d} \sim Dir\left(\delta\right)$.
    b) choose a distribution of sentiment global topics $\theta^{gl}_{d,l} \sim Dir\left(\alpha^{gl}\right)$.

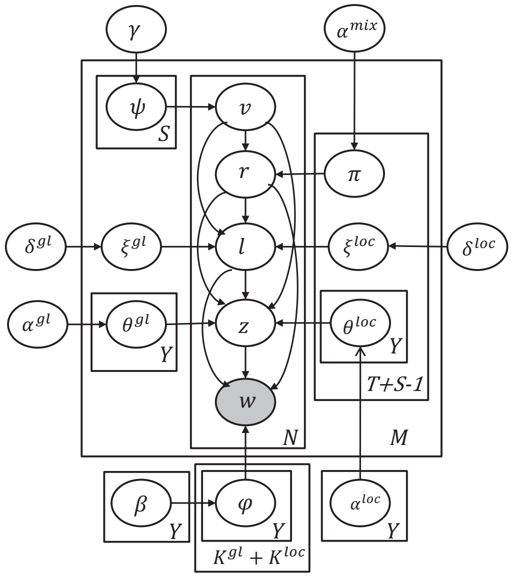

Fig. 2. Graphical Representation of JMTS Generative Process.

c) For each sentence *s*, choose a categorical distribution $\psi_{d,s}(v) \sim \textit{Dir}(\gamma)$.

d) For each window *v*,
   - choose a distribution of local topics $\theta^{loc}_{d,v,l} \sim Dir\left(\alpha^{loc}\right)$,
   - choose a distribution of topic mixture $\pi_{d,v} \sim Beta\left(\alpha^{mix}\right)$; noting that $Beta\left(\alpha^{mix}\right)$ is a continuous Beta distribution with the Beta prior in the topic mixture distribution, α^{mix},
   - choose a sentiment distribution $\xi^{loc}_{d,v} \sim Dir(\delta)$,

e) For each word *w* in sentence *s*,
   i) choose a window $v \sim \psi_{d,s}(v)$; noting that $\psi_{d,s}$ is categorical distribution in step 2.c,
   ii) choose a context $r \sim \pi_{d,v}$; noting that $\pi_{d,v}$ is topic mixture distribution in step 2.d.(ii),
   iii) If context *r* equal to global,
      - choose a sentiment label $l \sim \xi^{gl}_{d}$; noting that ξ^{gl}_{d} is sentiment distribution in step 2.a,
      - choose a sentiment global topic $z \sim \theta^{gl}_{d,l}$; noting that $\theta^{gl}_{d,l}$ is sentiment global topics distribution in step 2.b,
   iv) If context *r* equal to local,
      - choose a sentiment label $l \sim \xi^{loc}_{d,v}$; noting that $\xi^{loc}_{d,v}$ is sentiment distribution in step 2.d.(iii),
      - choose a sentiment local topic $z \sim \theta^{loc}_{d,v,l}$; noting that $\theta^{loc}_{d,v,l}$ is local topic distribution in step 2.d.(i),
   v) Draw a word $w \sim \varphi^{r}_{z,l}$; noting that $\varphi^{r}_{z,l}$ is context sentiment topic-word distribution.

IV. Experiment

A. Dataset

There are two ways for collecting the tweets, the Twitter firehose and Twitter streaming API. The Twitter firehose is able to provide 100% of all public tweets. However, this method is expensive and not publicly available. The Twitter streaming API, on the other hand, is freely provided by Twitter to collect up to 1% sample of the global stream of tweet data. The Twitter streaming API will find tweets that match the given parameters and/or keywords, and when the result surpasses 1% limit, it will randomly sample the result and deliver the sampling result to the client. In our experiment, we collect the tweet data using Twitter streaming API[1].

We collect English tweets for one week period in two ways. First, we collect all English tweets return by streaming API. We refer this dataset as *general dataset*. The data was collected during October 19-25, 2013, and we collected approximately 810 MB of data containing 8.6 million tweets in general dataset. Separately, we apply keywords filtering to the streaming API[2]. The purpose is to get dataset that is more focused on certain topic. The keywords we use are related to Apple Inc. products, such as iPad, iPhone iPad, OS X Maverick, Macbook, etc. We refer this dataset as *filtered dataset*. The data was collected during October 24-30, 2013, and we collected approximately 313 MB of data containing 2.56 million tweets. Both general and filtered dataset are preprocessed with stemming using the Porter stemmer and undergo stopwords removal. The summary of the dataset profile is presented at Table I.

B. Environment

We run our experiment on a machine powered by Intel(R) Xeon(R) CPU E5620 1.40GHz processor with 32GB of memory and run under Ubuntu Server 10.04 LTS 64bit operating system.

C. Ground Truth Trends

In our experiment, the ground truth trends are a set of actual trends which exist within the dataset. Each of them is represented with one or more defining terms. We use ground truth trends as the basis of evaluation by comparing them with the results of the three methods described in Section 3.

We use the terms extracted from the three methods as the starting point for constructing the ground truth trends; however, we only select those that seem to have topical value. Then, we manually lookup to the Twitter website and the Internet to verify whether these keywords belong to any topics (such as events, news, person, etc). If they do, we add the topic to the list of ground truth trends and include the keywords as the defining terms.

Since the topic of discussion in Twitter dynamically changes, the ground truth trends vary from day to day. The variation is more apparent in the general dataset than in the

[1]https://dev.twitter.com/docs/streaming-apis/connecting
[2]https://dev.twitter.com/docs/streaming-apis/parameters

TABLE II
PERFORMANCE EVALUATION FOR GENERAL DAY 4 DATASET

	Ground Truth Trends	Trend's defining terms	FP	LDA	JMTS lc	JMTS gl
1.	Justin Beiber	hold tight @justinbieb justin beiber #46millionbelieb	✓		✓	✓
2.	Android Game	#android #androidgam				✓
3.	One Direction	one direction @nialloffici @louistomlinson @harrystyl 1D @onedirection				✓
4.	Demi Lovato	#letitgo @ddlovato #demifrozen		✓		
5.	iPad game	#ipad #ipadgame gold coin #gameinsight				✓
6.	Katy Perry	@katyperri				✓
7.	Football	josh freeman @sportscent football season player game				✓
8.	Fifth Harmony	@allybrook			✓	
9.	US Government	state countri america nation office american obama obamacare				✓
10.	Halloween	halloween costum			✓	✓
11.	Miley Cyrus	milley cyrus wreck ball		✓	✓	
12.	TLC Movie	tlc movie left eye lil mama keke palmer #crazysexycool #tlcmovie @officialchilli #vh1 @vh1	✓	✓	✓	✓
			2	3	5	8

TABLE III
ACCURACY PERFORMANCE (F_1) FOR GENERAL DATASET

Dataset	FP (%)	LDA (%)	JMTS lc (%)	JMTS gl (%)
Day 1	12.7	38.1	38.7	37.5
Day 2	12.3	49.3	32.3	58.8
Day 3	19.7	23.2	41.4	37.5
Day 4	20.5	20.5	44.4	56.3
Day 5	25.9	32.0	27.6	54.5
Day 6	13.3	33.8	34.5	51.6
Day 7	6.3	51.7	45.2	60.6
Average	15.8	35.5	37.7	51.0

TABLE IV
EXTRACTED BIGRAMS BY FREQUENT PHRASE FOR GENERAL AND FILTERED DATASET ON OCTOBER 24^{th}, 2013

Dataset	Extracted Trends
General Day 6	todai stat, im not, unfollow follow, dont know, happi birthdai, follow, new follow, feel like, cant wait, look like, follow unfollow, stat follow, iv collect, follow no, no unfollow, ***#android #androidgam***, follow 2, ***gold coin***, no new, follow person, im go
Filtered Day 1	***#ipad #ipadgam***, iv collect, ***gold coin***, iv harvest, ***ipad air***, ***#ipad game***, ***game tribez***, ***os x***, ***complet quest***, ***ipad mini***, ***x maverick***, ***mysteri manor***, ***#csr-classic ipad***, discov locat, street london, ***new ipad***, iv complet, hurrai iv, ***quest mysteri***, ***manor game***

filtered dataset as the filtered dataset has a more focused content. The example of ground truth trends of general and filtered dataset can be found in Table II and Table V, respectively.

D. Performance Metrics

In information retrieval, precision is the fraction of retrieved instances that are relevant, while recall is the fraction of relevant instances that are retrieved. If T is the collection of topics which are extracted from Twitter corpus and GT is the collection of the ground truth trends, then we calculate precision as:

$$Precision = \frac{|GT \cap T|}{|T|}. \quad (1)$$

and recall as:

$$Recall = \frac{|GT \cap T|}{|GT|}. \quad (2)$$

F_1 combines both precision and recall to calculate the model accuracy by this formula:

$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}. \quad (3)$$

V. RESULT

A. Extracting Twitter Trends

1) Frequent Phrase: We count the bigrams occurrence in dataset and rank them accordingly. For each daily dataset, we select top-20 bigrams and compare them to the ground truth trends to determine how many bigrams correspond to those trends.

2) LDA and JMTS: LDA extracts 100 topics from the daily dataset. Each topic is represented by top 20 words with the highest distribution in that topic. However, these topics aren't returned in any particular order. Therefore, we perform further computation to find and rank which topics have the highest distribution (i.e. occurred the most) within the daily dataset. We select the top-20 topics for each daily dataset and examine them against the ground truth trends to determine how many topics LDA extracted correspond to ground truth trends.

We perform similar method for extracting trends using JMTS. JMTS returns 100 topics, which are a mix of 80 global and 20 local topic. We rank the JMTS topics and select top-20 global topics and top-20 local topics for each daily dataset. Again, we cross-examine them with the ground truth trends

TABLE V
PERFORMANCE EVALUATION FOR FILTERED DAY 3 DATASET

	Ground Truth Trends	Trend's defining terms	FP	LDA	JMTS lc	JMTS gl
1.	iPad Game	game #gameinsight #ipadgam gold coin	✓		✓	✓
2.	New iPad	ipad air mini retina display hd	✓		✓	✓
3.	OS X Maverick	os x maverick osx #osxmaverick		✓	✓	✓
4.	Giveway Events	win free chanc win spooktacular #giveawai #acesupportsbomfla #uliveyouwin @goodrichquality		✓	✓	
5.	Product review	#reviewthebest @reviewthebest #productreview @cnet				✓
6.	iBook	ibook #welcometoparadise @codysimpson		✓	✓	✓
7.	'Airport City' (Game Tittle)	engin airport airborn stewardess captain jack			✓	✓
8.	'The Tribez' (Game Tittle)	tax coll barista chief elder lord landscap flaker mansion flower-beed bench brazier firewood guardian stolen mission plant weed bush pretti bush jamboa igloo	✓	✓	✓	✓
9.	'Mystery Manor' (Game Tittle)	mysteri manor queen hermit librari	✓	✓		✓
10.	'CSR Classics' (Game Tittle)	csrclassic car impala #paintjob race	✓	✓	✓	✓
11.	'Mirrors of Albion' (Game Tittle)	boudoir airship bellini street london jonathan night walrus jane wright rainbow thomson	✓	✓	✓	✓
12.	iMac	imac mac computer desktop		✓	✓	
13.	Macbook	macbook pro			✓	
14.	iPhone	iphone #iphone iphone5		✓	✓	✓
15.	iBook	ibook #welcometoparadise @codysimpson		✓	✓	✓
16.	Troubleshooting	fix problem issue upgrade update crash trouble bug install		✓	✓	✓
17.	Jailbreak	jailbreak				✓
18.	Product specifications	netbook touchpad 10inch price usb device 16gb gb wireless storage 500gb safari battery io keyboard laptop charger 80211ac wifi		✓	✓	✓
19.	Media	@pcmag @mashable @macworld		✓		✓
20.	'Legacy of Transylvania' (Game Tittle)	transilvania legaci			✓	✓
21.	'Love and Dragon' (Game Tittle)	dragon miralda herbalist davian dragonblossom		✓	✓	✓
22.	Carrier operator	tmobile @tpouk		✓		
			6	15	17	18

to find how many global and local topics JMTS extracted correspond to the ground truth trends.

B. General Dataset

From all seven daily general datasets, the frequent phrase's bigrams are only able to capture five distinct trends, which are 1) mobile gaming on Android platform, 2) Justin Beiber, 3) biographic movie of US girlband TLC titled 'CrazySexyCool: The TLC Story', 4) British boyband One Direction, and 5) TV Series 'Pretty Little Liar'. The rest of the bigrams (such as: *todai stat*, *unfollow follow*, *im not*, *feel like*, *happi birthdai*, etc.) have no topical value despite of having high number of occurrence. These meaningless bigrams are noises which are caused by the conversational nature of Twitter corpus.

Both LDA and JMTS are able to extract more unique trends than the frequent phrase. However, among those daily top-20 topics, we find considerable amount of topics which have no meaningful topical value. For example is this particular topic represented by the following words: *great*, *amaz*, *hope*, *idea*, *better*, *proud*, *wonder*, *enjoi*, *talk*, *awesom*, *inspir*, *talent*, *sound*, *everyon*, *night*, *experi*, *glad*, *fantast*, *charact* and *even*. However, this topic represents emotional value of the dataset.

Table II shows performance evaluation of the three techniques on General Day 4 dataset. We manually check the top-20 bigrams from frequent phrase to see if any of them are presented in the ground truth trends' defining terms. If yes, we mark that the respective trend is detected by frequent phrase. We repeat that step for each LDA, JMTS global and local topics. Then, we count the number of detected trends for each techniques and calculate its accuracy. We evaluate other daily general datasets in similar way, but we have to omit them due to space limitations. The ground truth trends varies (12-16 trends, average 13 trends) for each daily general dataset.

We present the accuracy of the three techniques in extracting trends from general dataset for seven days in Table III. Since the frequent phrase only extracts so few trends, it is expected that this model scores the lowest accuracy. JMTS global and local topic outperforms LDA by 2.2% and 15.5%, respectively. We note that despite the high level of conversational noises, JMTS global topic manages to achieve accuracy level above 50%.

C. Filtered Dataset

Focusing the dataset proves to be effective in eliminating the conversational noise from Twitter corpus. In Table IV we

TABLE VI
ACCURACY PERFORMANCE (F_1) FOR FILTERED DATASET

Dataset	FP (%)	LDA (%)	JMTS lc (%)	JMTS gl (%)
Day 1	32.2	64.4	76.2	88.9
Day 2	37.8	70.3	81.1	81.1
Day 3	29.3	73.2	85.0	90.5
Day 4	31.6	63.2	68.4	73.7
Day 5	25.0	55.0	61.5	82.9
Day 6	30.8	51.3	76.9	82.1
Day 7	21.6	43.3	72.2	89.5
Average	29.8	60.1	74.5	84.1

compare the trends extracted by frequent phrase method from General Day 6 and Filtered Day 1 dataset, both collected at the same day (October 24^{th}, 2013). The decreasing number of meaningless bigrams is noticeable. However, frequent phrase suffers from high redundancy and overlapping. For example, four different bigrams of *#ipad #ipadgam*, *gold coin*, *#ipad game* and *complet quest* are actually referring to the same trend, 'iPad games'. Likewise, the results of both LDA and JMTS show fewer meaningless or ambiguous topics and more meaningful topics.

In evaluating the daily filtered dataset, we use the evaluation procedure as shown in Table V. The evaluation steps are similar to the evaluation procedure for daily general dataset. Table V shows the performance evaluation of Filtered Day 3 only. The other daily filtered datasets are evaluated in similar manner. We also observe the dynamical change in the number of ground truth trends in across seven daily filtered datasets. It varies between 19-27 trends, with average of 23 trends for each daily filtered dataset.

The accuracy performance for filtered dataset is presented in Table VI. Frequent phrase accuracy is the lowest among other techniques. It is caused by high number of redundancy and overlapping of the extracted bigrams. Both JMTS local and global topics outperform LDA by 14% and 34%, respectively. This is attributed to the fact that LDA returns more meaningless or ambiguous topics than JMTS. In fact, JMTS local and global topics consistently outperform LDA in across seven daily filtered datasets. Tabel VI shows JMTS global topics outperforms JMTS local, as it is also observed previously in general dataset. Therefore, we draw an conclusion that when JMTS is applied on data with very high topic diversity like Twitter corpus, the global topics perform better in discovering the trending topics.

VI. CONCLUSION

In this paper, we examine the performance of three models for extracting Twitter trends: frequent phrase, LDA, and JMTS. We conduct our extensive experiment with two datasets, general and filtered dataset. High level of conversational noise, which is inherent in general Twitter dataset, degrades the performance of trends extraction.

In general dataset, JMTS global topics outperforms frequent phrase and LDA by 35% and 15%, respectively. In filtered dataset, JMTS global topics outperforms frequent phrase and LDA by 54% and 24%, respectively. Therefore, we claim that JMTS is the effective method in extracting trends on a noisy text data with a high level of topic diversity like Twitter corpus.

JMTS can capture the sentiment aspect of a corpus. This ability is not addressed in this paper but we plan to find the sentiment of Twitter trends using JMTS in the future.

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