

# Short Text Feature Enrichment

--Using Link Analysis on Topic-Keyword Graph

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# Outline

- **Introduction**
- **Our Method**
  - **Short Text Modeling with Topic Model**
  - **Re-rank Keywords under Topics**
  - **Construct Topic-keyword Graph**
  - **Extract Candidate Keywords**
  - **Expand Short Text**
- **Evaluation**
- **Conclusions**

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# Introduction



现在正在观看的视频



Modern Warfare 2: OpTic Nation-  
OpTic H3CZ Storm ...



Modern V  
Camping  
观看次数:  
machinmare



Vuvuzela  
Algerie)  
观看次数:  
guettab



## Search Hotels

Where?

Q e.g. hotel name or city

Check-in date

Day Month

Check-out date

Day Month

Rooms

adults children

Room 1: 2 0

+ Add another room

Search

Over 162,239 hotels worldwide

Up to 75% off hotels in 110 countries

No booking fees

More than 10,230,000 reviews

## Popular destinations



Rome

Italy

1320 hotels

Latest booking: 26 seconds ago



Las Vegas

USA

149 hotels

Latest booking: 6 seconds ago



# Introduction (contd.)

- The Explosion of
  - e-commerce, online communication, & online publishing, products ordering...
- Typical Examples
  - Web search snippets
  - Short messages, advertising messages
  - Book/movie summaries
  - Product descriptions & customer reviews
  - News feeds
  - Forum/chat messages
  - *Sina* micro-blog, twitter.
  - Descriptions of entities: people, companies, hotels, etc

# Introduction (contd.)

## ➤ Challenges

- Compared with normal text,
  - Noise (class irrelevant), Irregular
  - Short and Sparsity
  - Less topic-focused
- Especially for BOW,
  - ignores the textual information
  - lacks semantic knowledge
  - Less co-occurrences

## ➤ Existing Work

- Phan www'2008:
  - Learn LDA based on Wikipedia as external corpus;
  - Make inference on short text collection;
  - Expand and enrich the short text;
  - better similarity measurement;



**WIKIPEDIA**  
*The Free Encyclopedia*

# Introduction (contd.)

- **Existing Work (contd.)**
  - Chen et al. AAAI'2011
    - Improved by learning multi-granularity topics
  - Yan et al. www'2013
    - proposed a biterm topic model;
    - model topics over the whole corpus instead of document-level.
  - Zhu et al. UAI'2011
    - present a non-probabilistic topic modeling method, which can control the sparsity.
  - Sun SIGIR'2012
    - A simple method using representative words as query to search a few of labeled samples, and the majority vote of the search results is the predictable category.
  - Gabrilovich IJCAI'2007
    - a method to improve text classification performance by enriching document representation with Wikipedia concepts

# Our Framework

## ➤ Our framework based on TM & Link Analysis,

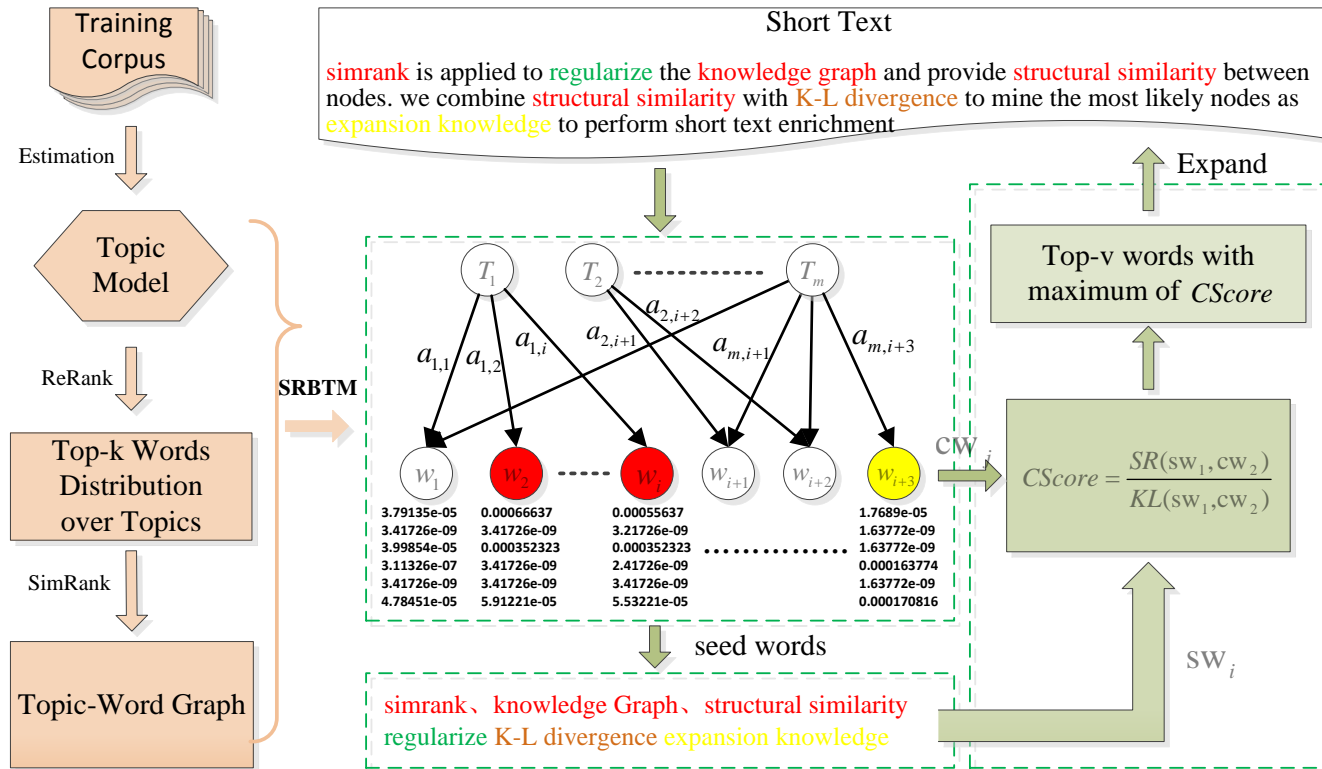


Fig 1. Method for short text expansion



# Short Text Modeling with Topic Model

## ➤ Blei et.al. JMLR'2003

- firstly proposed LDA and used it to estimate multinomial observations by unsupervised learning.
- based on an assumption of document generation process,

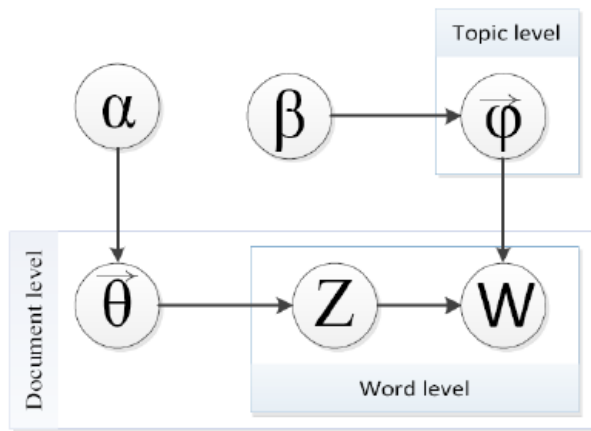


Fig.2 Grapical model of LDA

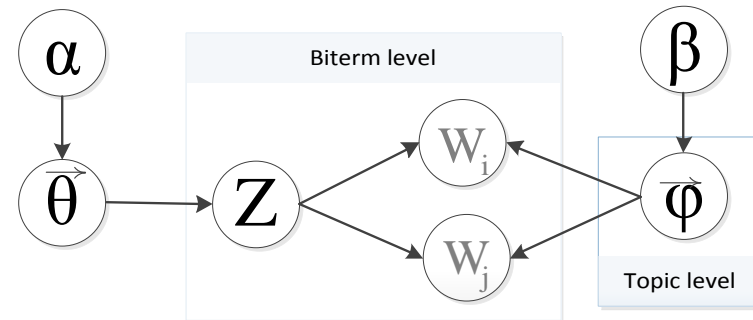


Fig.3 Grapical model of BTM

## ➤ Yan et al. www'2013

- Based on LDA, proposed BTM especially for short text.
- Directly model the word co-occurrences in the whole corpus to make full use of the global information.

# Short Text Modeling with Topic Model

- To extract topics, we learn parameters of BTM.
- words from each topic are related,
- representation more topic-focused,
- to alleviate sparsity and noise .

**Table 2.** Most likely words of some topics

Topic0: music band rock album song songs released  
 Topic1: species food animals animal plants humans  
 Topic2: energy mass field quantum particles force  
 Topic3: india indian hindu pakistan sanskrit century  
 Topic4: blood body brain heart cells muscle syndrome  
 Topic5: water carbon oil chemical gas process oxygen  
 Topic6: government party president constitution  
 Topic7: power energy solar electric electrical  
 Topic8: system data code software computer  
 Topic9: horse opponent horses body hand match  
 Topic10: south africa united country islands world

**Table 1.** Variables in BTM

Para.	Details
$M$	number of bi-terms
$\alpha, \beta$	Para. for <u>Dirichlet</u>
$\bar{\theta}$	topic distribution
$z$	index of a topic
$\bar{\varphi}_{i:z}$	$i$ <u>th</u> word distribution
$V$	vocabulary size
$K$	the number of topics
$\Phi$	a $K \times V$ matrix
$BT$	corpus with $M$ <u>biterms</u>

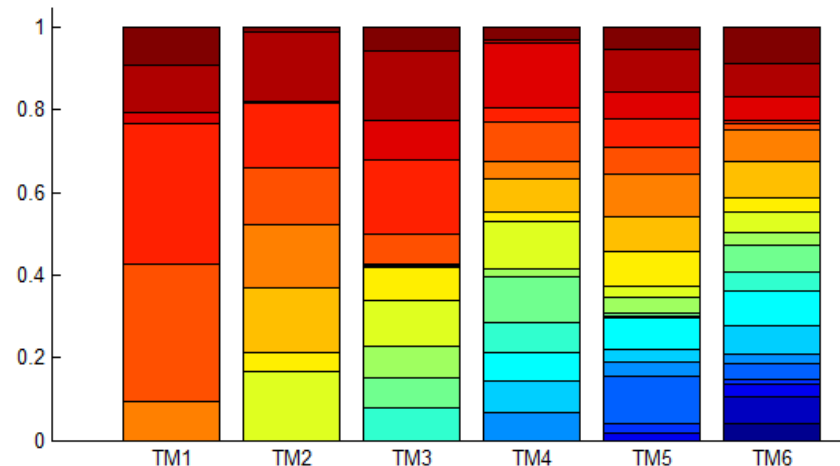


Fig.4 Topic distribution over keywords

# Re-rank Keywords under Topics

- The long tail like distribution of keywords under topics,

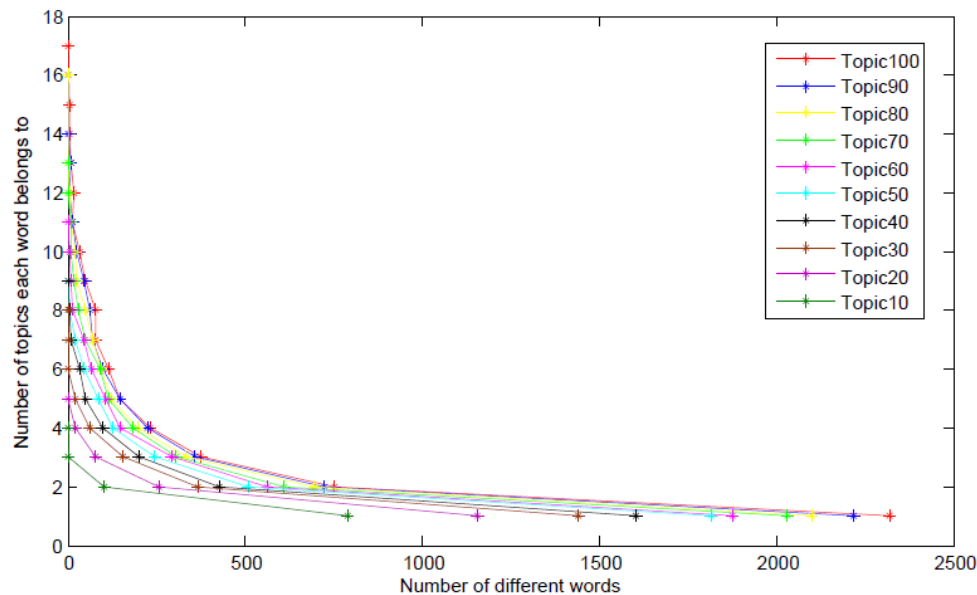


Fig.5 The keywords distribution under topics

$$SAS = \frac{e^{\hat{\varphi}_{z,i}}}{\sum_{m=1}^M e^{\hat{\varphi}_{z,i}}} \quad (1)$$

where  $\hat{\varphi}_{z,i}$  is the probability distribution of the  $i$ th word under topic  $k$ .

# Construct Topic-keyword Graph

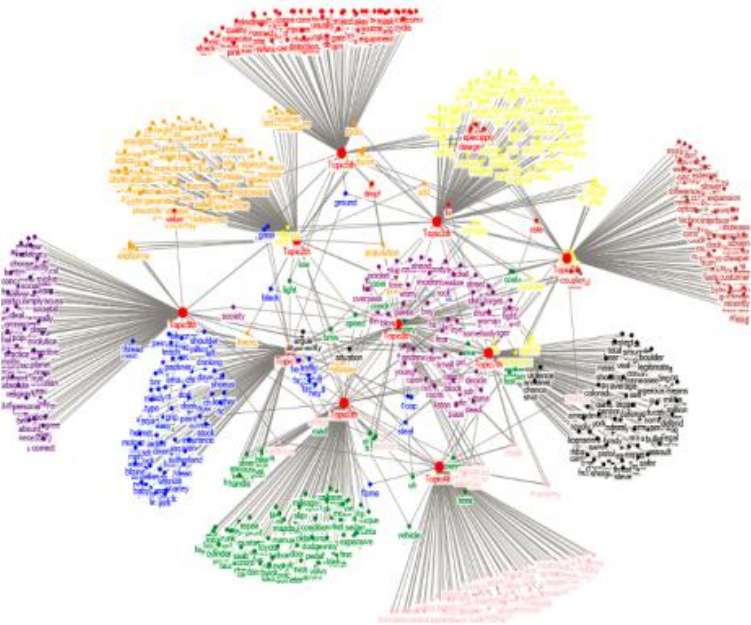


Fig.6 native topic-keyword graph

Re-Rank

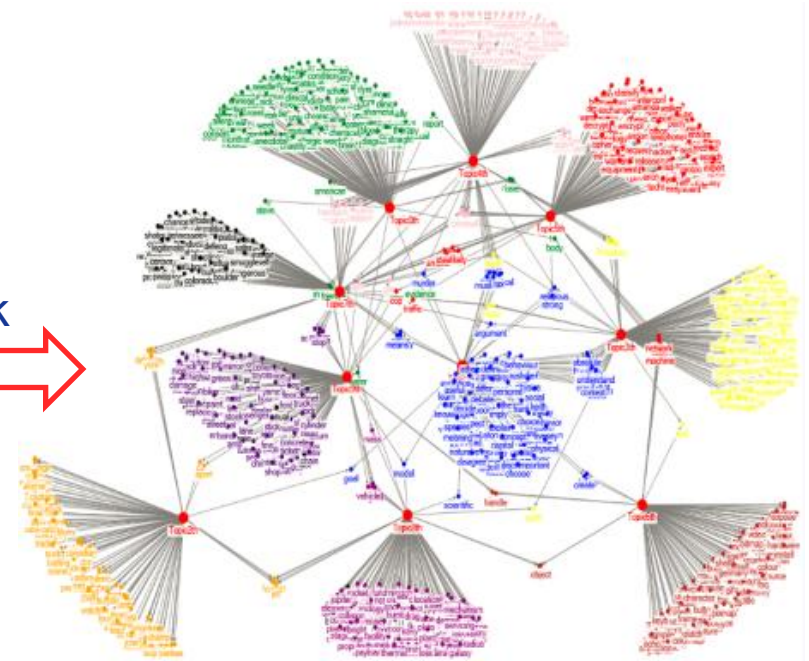
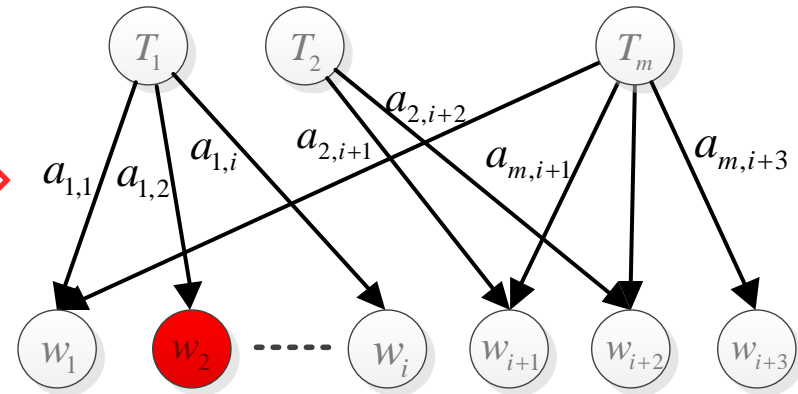
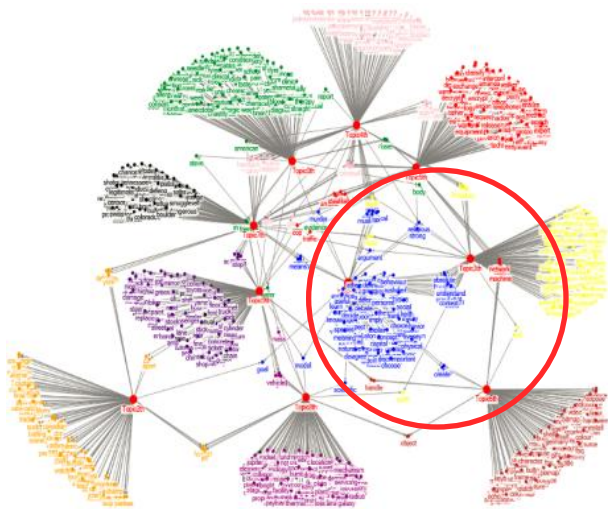


Fig.7 re-Ranked topic-keyword graph

# Extract Candidate Keywords

## Link Analysis:



$$s(w_a, w_b) = \begin{cases} 1 & , \quad \text{if } w_a = w_b \\ \frac{C}{|I(w_a)||I(w_b)|} \sum_{i=1}^{|I(w_a)|} \sum_{j=1}^{|I(w_b)|} s(I_i(w_a), I_j(w_b)), & \text{if } w_a \neq w_b \end{cases} \quad (2)$$

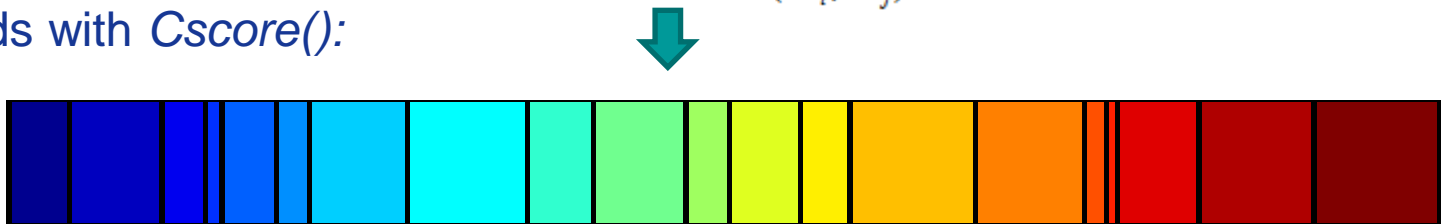
# Expand Short Text

$$SR(w_a, w_b) = SAS(w_a)SAS(w_b)s(w_a, w_b), \quad (3)$$

$$KL(sw_i, cw_j) = \frac{1}{2} [D(p_{sw_i}^{(z)} \parallel \frac{p_{sw_i}^{(z)} + p_{cw_j}^{(z)}}{2}) + D(p_{cw_j}^{(z)} \parallel \frac{p_{cw_j}^{(z)} + p_{sw_i}^{(z)}}{2})] \quad (4)$$

$$CScore(sw_i, cw_j) = \frac{SR(sw_i, cw_j)}{KL(sw_i, cw_j)}, \quad (5)$$

Keywords with Cscore():



Provided that,

$\vec{w}_m = \{ \text{Modeling short text based on Wikipedia and LDA} \}$

$\vec{w}_m = \{ \text{Modeling short text based on Wikipedia and LDA} \quad \text{[Colorful bar]} \}$

Original feature

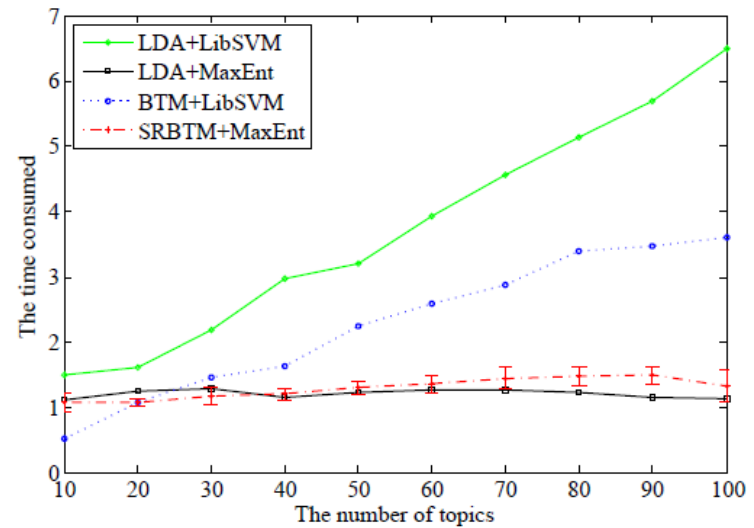
Expanded info.

# Evaluation

## ❖ *Experimental data*

- ❖ Search snippets dataset, consists of 10,060 training snippets and 2,280 test snippets from 8 categories, as shown in Table 3. On average, each snippet has 18.07 words

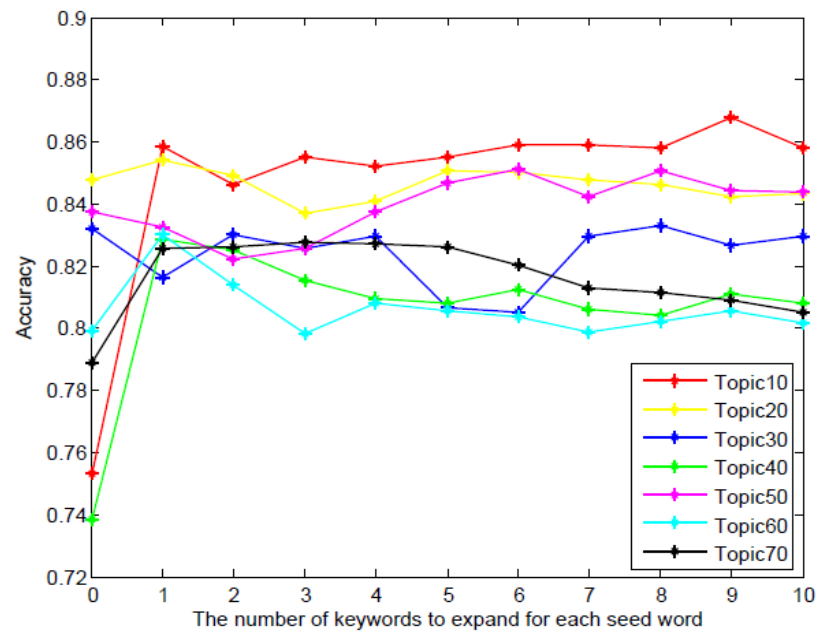
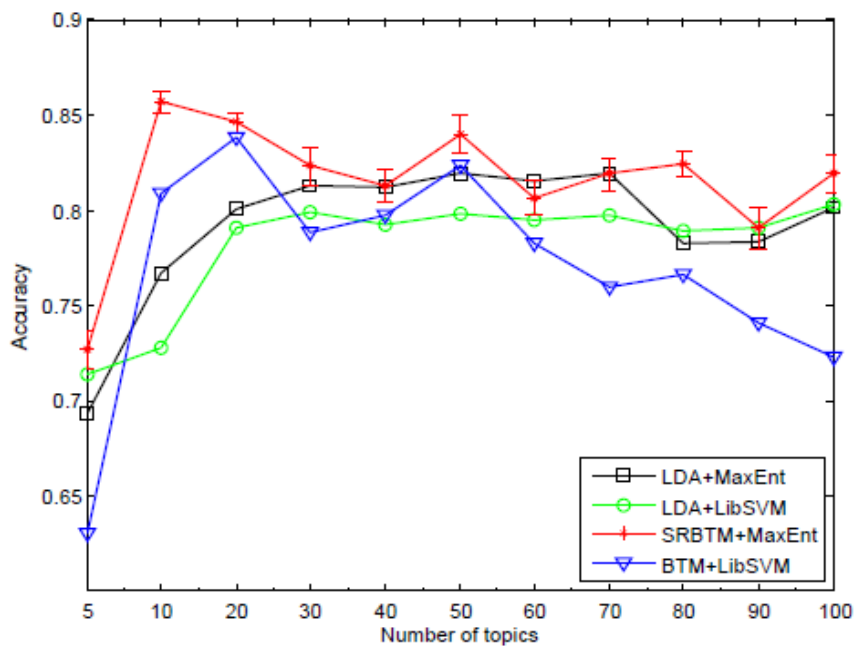
Domain	Tr snippets	Te snippets
Business	1200	300
Computers	1200	300
Cult.-arts-ente.	1880	330
Edu.-Science	2360	300
Engineering	220	150
Health	880	300
Politics-Society	1200	300
Sports	1120	300
<b>Total</b>	<b>10060</b>	<b>2280</b>



- Collected by Phan professor.
- Used in Phan and Nguyen WWW'2008, Chen et al. AAAI'2011;

# Evaluation

## ❖ Experimental Results:





# Conclusions

## ➤ Achievements

- Re-rank the candidates keywords under topics;
- Construct the topic-keywords graph;
- Extract keywords using link analysis;
- Expand the short text by Keywords.

## ➤ Remaining Issues

- The BTM is time-consuming;
- Noise is still may be introduced.

*Thanks For Your Time !*

