A Probabilistic Model for Bursty Topic Discovery in Microblogs

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Bursty Topics in Microblogs

Bursty topics: novel topics attracting wide interest (hot events, activities, discussions)

Valuable information

public opinion analysis  business intelligence  news clues tracking  Message recommendation
Problems & Challenges

- Microblog Posts are very short
  - Conventional topic models (e.g., LDA and PLSA) are not effective over short texts
  - How to discover topics in such short texts?

- Microblog Posts are very diverse and noisy
  - Lots of pointless babbles, daily chatting and other non-bursty content
  - How to distinguish bursty topics from other topics?
Our Work

- We propose a probabilistic model to solve the two challenges in a principled and effective way

How to learn topics over short texts?
Exploit the rich global word co-occurrence to learn topics
(following our previous work biterm topic model)

How to distinguish bursty topics from non-bursty content?
Exploit the burstiness of biterms as prior knowledge for bursty topic discovery
Biterm Topic Model (BTM) for Short Texts
(Yan et.al WWW’13)

- LDA will encounter the data sparsity problem when docs are short
- **BTM models the generation of biterm**
  - Drawn a topic $z$ from a global topic distribution $\theta$
  - draw two word from the topic $z$
- **BTM can better learn topics over short texts**
  - Directly model the word co-occurrence
  - fully exploit the rich global word co-occurrence to overcome the data sparsity problem in short documents

But BTM learns general topics rather than bursty topics 😞
Observations

- A **bursty biterm** is **more** likely to be generated from some bursty topic
  
  ![Graph](image)
  
  bursty topic about the World Cup 2014

- A **non-bursty biterm** is **less** likely to be generated from any bursty topics
  
  ![Graph](image)
  
  Non-bursty topic
Bursty Probability of a Biterm

- How likely a biterm will be generated from some bursty topic?

Suppose each biterm is generated either from some bursty topic or other non-bursty topic

- $n_{b}^{(t)}$ can be estimated by the average count in the last S time slices

$$n_{b,0}^{(t)} = \min\left(\frac{1}{S} \sum_{s=1}^{S} n_{b}^{(t-s)}, n_{b}^{(t)}\right)$$

$$\eta_{b}^{(t)} = \frac{n_{b,1}^{(t)}}{n_{b}^{(t)}} = 1 - \frac{n_{b,0}^{(t)}}{n_{b}^{(t)}}$$
1. For the collection,
   - draw a bursty topic distribution $\theta \sim \text{Dir}(\alpha)$
   - draw a background word distribution $\phi_0 \sim \text{Dir}(\beta)$
2. For each bursty topic $k \in [1, K]$,
   - draw a word distribution $\phi_k \sim \text{Dir}(\beta)$
3. For each bitem $b_i \in \mathbb{B}$
   - draw $e_i \sim \text{Bern}(\eta_{b_i})$
   - If $e_i = 0$,
     - draw two words $w_{i,1}, w_{i,2} \sim \text{Multi}(\phi_0)$
   - If $e_i = 1$,
     - draw a bursty topic $z \sim \text{Multi}(\theta)$
     - draw two words $w_{i,1}, w_{i,2} \sim \text{Multi}(\phi_z)$
Parameter Inference by Gibbs Sampling

- Randomly assign a topic for each biterm
- Repeatedly update the topic for each biterm in a sequential way until convergence

\[
P(e_i = 1, z_i = k | e^{-i}, z^{-i}, \mathbb{B}, \alpha, \beta, \eta) \propto \eta_{b_i} \cdot \frac{(n_k^{z_i} + \alpha)}{(n^{z_i} + K\alpha)} \cdot \frac{(n_k^{e^{-i}} + \beta)(n_k^{e^{-i}, w_{i,1}} + \beta)}{(n_k^{e^{-i}} + W\beta)(n_k^{e^{-i}} + 1 + W\beta)}
\]

BBTM always choose the bursty and relevant biterms to construct bursty topics
Experiments

- **Trec Tweets2011 Collection**
  - 17 days: 2011.1.23-2011.2.8
  - 4,230,578 tweets, 98,857 distinct terms

- **Baselines**
  - Twevent: state-of-the-art heuristic-based approach
  - oLDA: online LDA + post-processing
  - UTM: User Temporal Topic Model, state-of-the-art model-base approach
  - IBTM: BTM + post-processing
  - BBTM-S: draw $e_i$ in the first iteration and then fix it
Accuracy of Bursty Topics

**Metric:** Precision@$K_1$

<table>
<thead>
<tr>
<th>Method</th>
<th>P@10</th>
<th>P@30</th>
<th>P@50</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twevent</td>
<td>0.592</td>
<td>0.681</td>
<td>0.636</td>
</tr>
<tr>
<td>UTM</td>
<td>0.565</td>
<td>0.488</td>
<td>0.453</td>
</tr>
<tr>
<td>OLDA</td>
<td>0.231</td>
<td>0.217</td>
<td>0.185</td>
</tr>
<tr>
<td>IBTM</td>
<td>0.300</td>
<td>0.325</td>
<td>0.297</td>
</tr>
<tr>
<td>BBIM-S</td>
<td>0.789</td>
<td>0.832</td>
<td>0.790</td>
</tr>
<tr>
<td>BBTM</td>
<td>0.810</td>
<td>0.865</td>
<td>0.842</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$k$</th>
<th>The 10 most probable words</th>
<th>$\hat{\theta}_k$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>police officers shot shooting detroit twitter adam suspect year revenue</td>
<td>0.036</td>
</tr>
<tr>
<td></td>
<td>(Two St. Petersburg police officers were shot and killed)</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>airport moscow police news killed people dead blast suicide explosion</td>
<td>0.057</td>
</tr>
<tr>
<td></td>
<td>(Deadly suicide bombing hits Moscow’s Domodedovo airport)</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>open #ausopen nadal australian murray mike tomlin cloud #cloud avril</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(Australian Open Tennis Championships 2011)</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>jack lalanne fitness 96 dies guru rip died age dead</td>
<td>0.044</td>
</tr>
<tr>
<td></td>
<td>(Jack Lalanne: US fitness guru who last ate dessert in 1979 dies aged 96)</td>
<td></td>
</tr>
<tr>
<td>26</td>
<td>court emanuel rahm chicago ballot mayor mayoral run appellate rules</td>
<td>0.024</td>
</tr>
<tr>
<td></td>
<td>(Court tosses Emanuel off Chicago mayoral ballot)</td>
<td></td>
</tr>
</tbody>
</table>
Coherence and Novelty of Bursty Topics

- **Coherence**
  - More relevant the top words in topics, the coherence is higher

- **Novelty**
  - More words are overlap between two time slices, the novelty is lower
Efficiency

<table>
<thead>
<tr>
<th>K</th>
<th>UTM</th>
<th>OLDA</th>
<th>IBTM</th>
<th>BBTM-S</th>
<th>BBTM</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>4.24</td>
<td>1.84</td>
<td>4.66</td>
<td>0.03</td>
<td>1.57</td>
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<tr>
<td>20</td>
<td>6.02</td>
<td>2.61</td>
<td>5.97</td>
<td>0.06</td>
<td>2.89</td>
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<tr>
<td>30</td>
<td>7.84</td>
<td>3.28</td>
<td>7.24</td>
<td>0.09</td>
<td>4.40</td>
</tr>
<tr>
<td>40</td>
<td>9.79</td>
<td>4.02</td>
<td>8.54</td>
<td>0.13</td>
<td>5.71</td>
</tr>
<tr>
<td>50</td>
<td>11.63</td>
<td>4.83</td>
<td>9.99</td>
<td>0.17</td>
<td>7.24</td>
</tr>
</tbody>
</table>

Table 4: Time cost (second) per iteration.

- BBTM-S costs much less time than other methods
  - since it only used a subset of biterms for training
- BBTM is more efficient than IBTM and UTM.
  - since they waste time to learn non-bursty topics
Summary

- We propose the bursty biterm topic model for bursty topic discovery in microblogs
  - It exploits the rich global word co-occurrence for better topic learning over short texts
  - It exploits the burstiness of biterms to distill bursty topics automatically

- Future works
  - Improve the estimation of bursty probability
  - Improve topic representations with external data
Thank You!

Code: https://github.com/xiaohuiyan/BurstyBTM
Our related work: http://shorttext.org/