Modeling Sentiment Evolution for Social Incidents

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Abstract

Modeling sentiment evolution for social incidents in Microblogs is of vital importance for both enterprises and government officials. Existing works on sentiment tracking are not satisfying, due to the lack of entity-level sentiment extraction and accurate sentiment shift detection. Identifying entity-level sentiment is challenging as Microbloggers often use multiple opinion expressions in a sentence which targets different entities. Moreover, the evolution of the background sentiment, which is essential to shift detection, is ignored in the previous study. To address these issues, we leverage the proximity information to obtain more precise entity-level sentiment extraction. Based on it, we propose to simultaneously model the evolution of background opinion and the sentiment shift using a state space model on the time series of sentiment polarities. Experiments on real data sets demonstrate that our proposed approaches outperform state-of-the-art methods on the task of modeling sentiment evolution for social incidents.

Problem Definition

Given a sequence of posts $d_0, d_1..., d_t$ related to any social incident, our goal is to reveal the sentiment evolution pattern related to the involved entity e in this incident and identify significant sentiment shifts.

Contributions

- Identify entity-level sentiment for finer analysis.
- Distinguish sentiment shift from background opinion evolution.

Proximity-based Entity-level Sentiment Extraction

Assumption: the closer a sentiment word is to an entity, the more likely that the sentiment word is describing the entity.
Classify the polarity y of sentiment towards an entity e_j in a post d:

$$y = \frac{\sum_{i=1}^{N}(-1)^{q_i} \cdot z_i \cdot v_i \cdot k(l_i, l_j)}{n}, \tag{1}$$

Notations	Description
y	sentiment polarity
N	the number of sentiment words
q_i	the number of negative words
z_i	the sum of degree value
v_i	sentiment value of ith sentiment word
k	distance kernel function
l_i	location of ith sentiment word
l_j	location of entity e_j

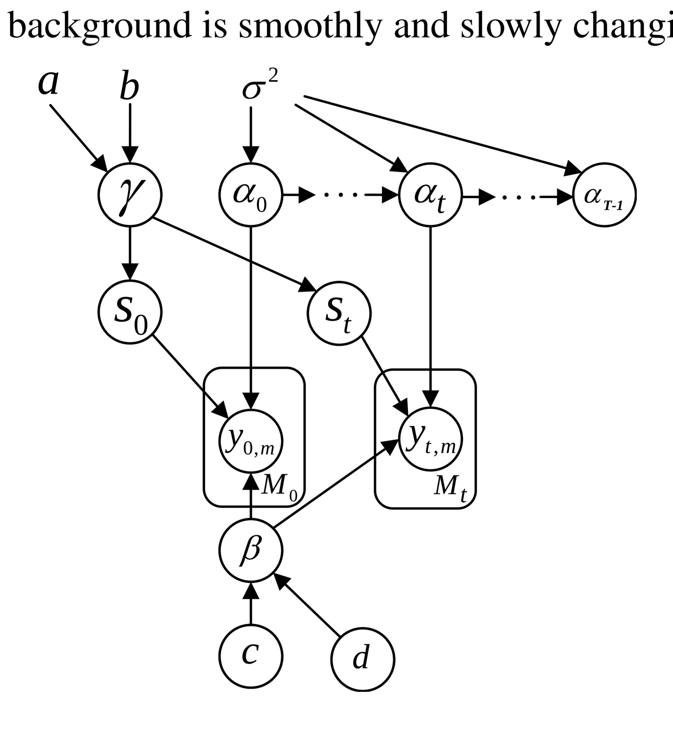
Four distance kernel functions, namely Gaussian, Triangle, Cosine (Hamming), and Circle.

- **Gaussian:** $k(l_i, l_j) = \exp\left[\frac{-(l_i-l_j)^2}{2\sigma^2}\right]$
- **Triangle:** $k(l_i, l_j) = \begin{cases} 1 - \frac{|l_i-l_j|}{\sigma} & \text{if } |l_i - l_j| \le \sigma \\ 0 & \text{otherwise} \end{cases}$
- **Cosine:** $k(l_i, l_j) = \begin{cases} \frac{1}{2}\left[1 + cos\left(\frac{|l_i-l_j|\cdot\pi}{\sigma}\right)\right] & \text{if } |l_i - l_j| \le \sigma \\ 0 & \text{otherwise} \end{cases}$
- **Circle:** $k(l_i, l_j) = \begin{cases} \sqrt{1 - \left(\frac{|l_i-l_j|^2}{\sigma}\right)} & \text{if } |l_i - l_j| \le \sigma \\ 0 & \text{otherwise} \end{cases}$

Public Sentiment Evolution Model

Two assumptions:

- There is a background sentiment distribution.
- The background is smoothly and slowly changing.



Notations	Description
a, b, c, d	Hyper-parameter
y	sentiment polarity
M_t	the number of posts in time slice t
s	switch variable
α_t	distribution of background sentiment in time slice t
β	sentiment shift distribution

Figure 1: Plate notation of the proposed PSEM model

The generation process of PSEM is as follows:

- For time slice $t = 0$, draw $\alpha_0 \sim (0, \sigma^2\mathbf{I})$.
- For time slice $t = 1 : T-1$, draw $\alpha_t \sim (\alpha_{t-1}, \sigma^2)$. As is a continuous and differentiable distribution, the evolution of background opinions is smooth and slow.
- Generate a global prior γ for the switch s_0, i.e. a variable that controls how likely the public sentiment is to change, by $\gamma \sim Beta(a, b)$.
- For each time slice
  - Generate a switch $s_t \sim Bern(\gamma)$
  - For each observation, generate
    $y_{t,m} \sim \begin{cases} Bern(\pi(\alpha_t)) & \text{if } s_t = 1 \\ Bern(\beta) & \text{if } s_t = 0 \end{cases}$

Data

The data set contains 889,110 Chinese posts related to 14 incidents from Weibo, 1,459,488 English posts related to 6 incidents from Twitter.

Performance of Entity-level Sentiment Extraction

Methods	Comments length					
	0-20 words		20-40 words		40+ words	
	Positive	Negative	Positive	Negative	Positive	Negative
SentiStrength	0.3774	0.5808	0.2254	0.3906	0.3938	0.3622
SentiStrength-SE	0.6014	0.6951	0.5040	0.5843	0.5752	0.6467
SentiCR	0.7953	0.7855	0.7911	0.7005	0.7404	0.7861
MCNN	0.8199	0.8068	0.8019	0.8060	0.8003	0.8082
RCNN	0.8284	0.8243	0.8291	0.8211	0.8393	0.8353
PESE-I	0.8038	0.8170	0.8011	0.8032	0.8034	0.8166
PESE-C	0.8242	0.8212	0.8269	0.8229	0.8249	0.8291
PESE-T	0.8302	0.8342	0.8398	0.8479	0.8470	0.8486
PESE-G	**0.8477**$^+$	**0.8588**$^+$	**0.8539**$^+$	**0.8771**$^+$	**0.8862**$^+$	**0.9289**$^+$

Table 1: Average accuracy of different sentiment extraction methods. All PESE variants perform better than competitors. Positive polarities are usually with lower accuracy. Most methods obtain increasing accuracy on longer posts

Performance of Public Sentiment Evolution

	POMS	LDA-KL	FB-LDA	PSEM
Precision	0.5950	0.7000	0.7750	**0.8950**$^+$
Recall	0.5265	0.6195	0.6858	**0.7920**$^+$

Table 2: Average precision and recall of different shift detective methods. PSEM achieves the best results.

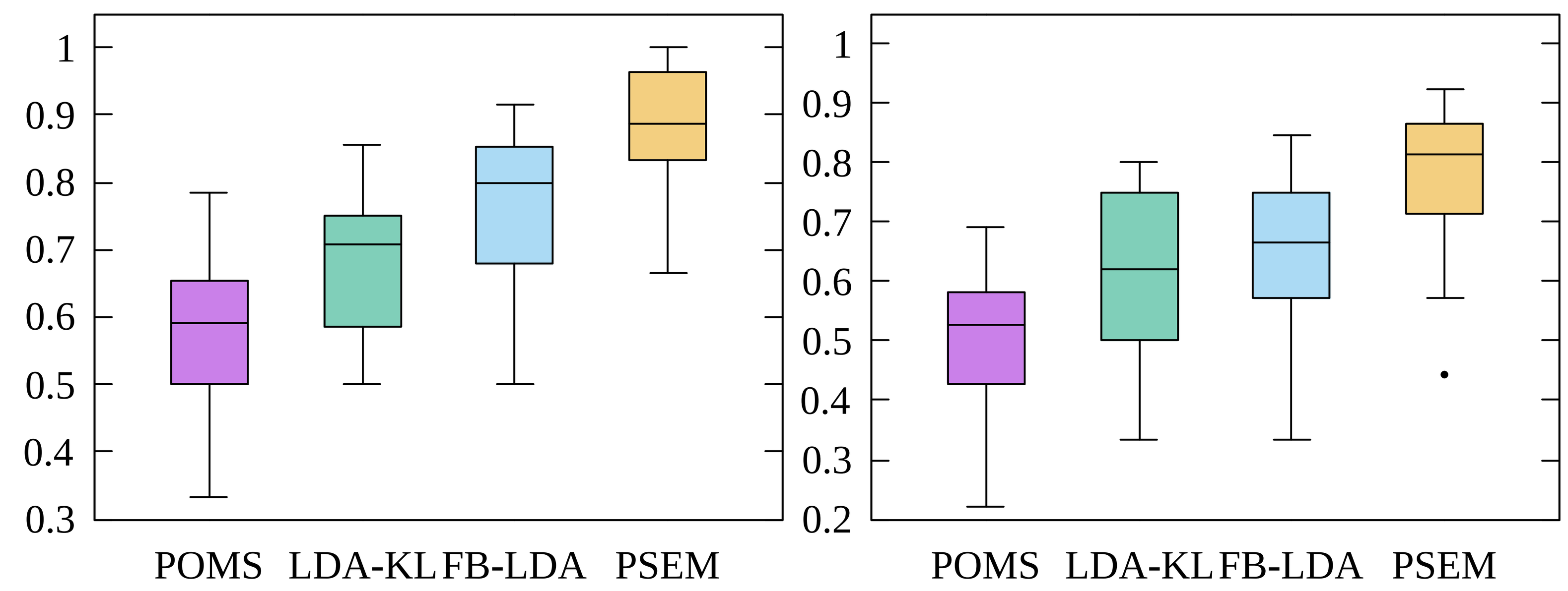


Figure 2: Comparison of performance on shift detection

Predictiveness of PSEM

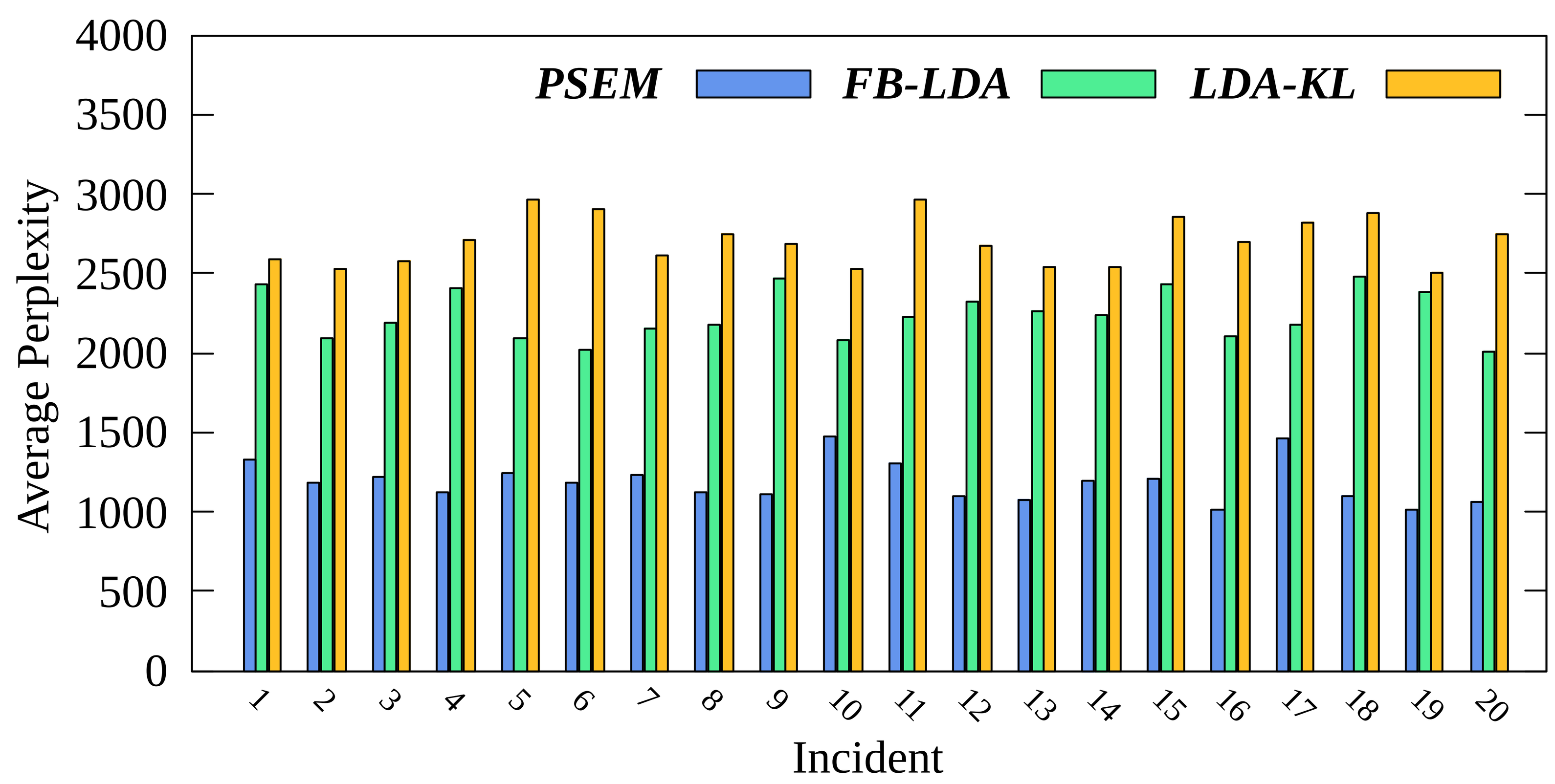


Figure 3: Average per-word predictive perplexity. PSEM has a better predictiveness

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