



Rumor Detecting with RNN

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Introduction



- Nowadays social platforms are becoming perfect places for rumors to spread.
- People post cues about one event over time, generating a long-distance dependencies of evidence.
- We want to find an approach to modeling the sequences of posts and judging whether an event is rumor.

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Data Process Dataset



- The experiment is based on a crawled Weibo dataset, which contains 3,805,656 posts and 4,664 events.
- There are 2,313 rumors and 2,351 non-rumors.

Data Process

Paragraphing



- The number of posts about an event can be huge and varied.
- An event may only be discussed heatedly for a short range of time.
- We need to find the time ranges where these events are heatedly discussed and paragraph them into sequences with similar length.

Data Process

Paragraphing



```

Input : Relevant posts of  $E_i = \{(m_{i,j}, t_{i,j})\}_{j=1}^{n_i}$ ,
          Reference length of RNN  $N$ 
Output: Time intervals  $I = \{I_1, I_2, \dots\}$ 

  /* Initialization */
1  $L(i) = t_{i,n_i} - t_{i,1}$ ;  $\ell = \frac{L(i)}{N}$ ;  $k = 0$ ;
2 while true do
3    $k++$ ;
4    $U_k \leftarrow \text{Equipartition}(L(i), \ell)$ ;
5    $U_0 \leftarrow \{\text{empty intervals}\} \subseteq U_k$ ;
6    $U'_k \leftarrow U_k - U_0$ ;
7   Find  $\bar{U}_k \subseteq U'_k$  such that  $\bar{U}_k$  contains continuous
   intervals that cover the longest time span;
8   if  $|\bar{U}_k| < N$  &&  $|\bar{U}_k| > |\bar{U}_{k-1}|$  then
   /* Shorten the intervals */
9      $\ell = 0.5 \cdot \ell$ ;
10  else
   /* Generate output */
11     $I = \{I_o \in \bar{U}_k | I_1, \dots, I_{|\bar{U}_k|}\}$ ;
12    return  $I$ ;
13  end
14 end
15 return  $I$ ;

```


Data Process

Vectorization



- Use tf-idf value to vectorize the paragraphs

$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}$$

$$idf_i = \log \frac{|D|}{|\{j : t_i \in d_j\}|}$$

$$tfidf_{i,j} = tf_{i,j} \times idf_i$$

- We take top-6000 words according to their tf-idf value as the dictionary.

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Modeling



- Simple LSTM
- Multi-layer RNN
- RNN with attention mechanism

Modeling



- We found that when the length of RNN(N) is less than 50, the performance is better when N is larger. And the performance began to drop when N is larger than 50.
- Use a simple attention to make the model able to deal with longer sequences.
- $a_i = f(H_i, x_{last})$

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Experiment



| Model | Accuracy | F1 Score | AUC |
|--------------------|----------|----------|--------|
| Simple LSTM | 0.9048 | 0.9024 | 0.9640 |
| Multi-layer RNN | 0.9119 | 0.9084 | 0.9668 |
| RNN with Attention | 0.9238 | 0.9223 | 0.9728 |

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- [1] Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural Machine Translation by Jointly Learning to Align and Translate, 1–15. <https://doi.org/10.1146/annurev.neuro.26.041002.131047>
- [2] Ma, J., Gao, W., Mitra, P., Kwon, S., & Jansen, B. J. (2016). Detecting Rumors from Microblogs with Recurrent Neural Networks Detecting Rumors from Microblogs with Recurrent Neural Networks, (July), 3818–3824.
- [3] Kim, J., Tabibian, B., Oh, A., Schoelkopf, B., & Gomez-Rodriguez, M. (2017). Leveraging the Crowd to Detect and Reduce the Spread of Fake News and Misinformation. <https://doi.org/10.1145/3159652.3159734>
- [4] Fan Yang, Yang Liu, Xiaohui Yu, and Min Yang. Automatic detection of rumor on sina weibo. In Proceedings of the ACM SIGKDD Workshop on Mining Data Semantics, 2012.

Thanks!

