PROJECT
DETECTING RUMORS FROM MICROBLOGS WITH RECURRENT NEURAL NETWORKS

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INTRODUCTION

- Microblogging platforms are an ideal place for spreading rumors and automatically debunking rumors is a crucial problem.
- False rumors are damaging as they cause public panic and social unrest.
- Many incidents of a false rumor highlight that automatically predicting the veracity of information on social media is of high practical value.

RUMOR REPORTING WEBSITES

- disadvantages:for manual verification steps are involved in such efforts, these websites are not comprehensive in their topical coverage and also can have long debunking delay
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EXISTING MODELS

DUSING LEARNING ALGORITHM

- They incorporate a wide variety of features manually crafted from the content, user characteristics, and diffusion patterns[1][2]of the posts or simply exploited patterns expressed using regular expressions to discover rumors in tweets

- Disadvantages: it is painstakingly detailed, biased, and labor-intensive.

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[1]Carlos Castillo, Marcelo Mendoza, and Barbara Poblete. Information credibility on twitter. In *Proceedings of WWW*, 2011.

[2]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.

[3]Sejeong Kwon, Meeyoung Cha, Ky- omin Jung, Wei Chen, and Yajun Wang. Prominent fea- tures of rumor propagation in online social media. In *Pro- ceedings of ICDM*, 2013.

REFERENCE PAPER METHOD

ALGORITHM

- Main work: Utilizing RNN, it model the social context information of an event as a variable-length time series. They assume people, when exposed to a rumor claim, will forward the claim or comment on it, thus creating a continuous stream of posts. This approach learns both the temporal and textual representations from rumor posts under supervision.
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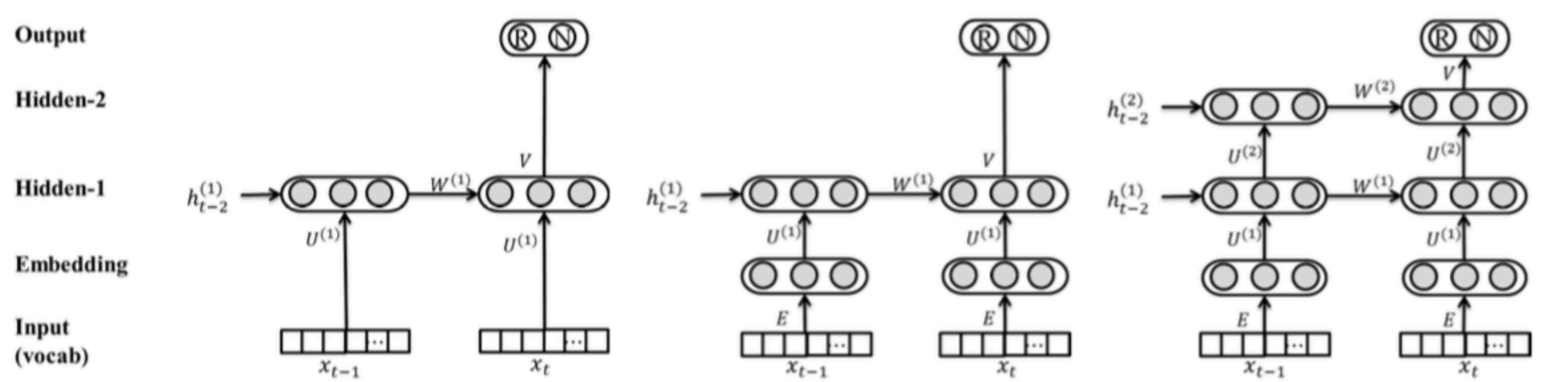
REFERENCE PAPER METHOD

MODEL



(a) Basic tanh-RNN (b) 1-layer LSTM/GRU + embedding (c) 2-layer GRU + embedding

REFERENCE PAPER METHOD

- In this model, there is a embedding layer that encode the origin representation of words into vector.
- However, in this paper, author did’t point out clearly the which is the input. the input is one word or a sentence, if it is one word, then the time step will be the longest length of top k
- if it is a sentence, then the time step will be the interval.

MY WORK

DATASETS

- Using datasets used by the reference paper
- After filtration, this dataset includes 4492 effective events and each event includes many post relevant to it.

MY WORK

DATA HANDING

- For each event, we divide the posts about this event into several continuous intervals and view this as the time steps of this event[4].

- for each interval in event, we split the sentences into word and use tfidf(Salton & McGill, 1983) algorithm to select top-k words during this interval then use these words as the representation of this interval.

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[4]MA J, GAO W, MITRA P, ET AL. DETECTING RUMORS FROM MICROBLOGS WITH RECURRENT NEURAL NETWORKS[C]//IJCAI. 2016: 3818-3824.

MY WORK

DATA HANDING

- for each words , we use a vector to represent it, and the cn_vector set is download from https://github.com/Embedding/Chinese-Word-Vectors in which we select the set trained from Weibo in which each word is represent by a vector of 300 length.
- Then we concat these vector of words to represent each interval . So for each events, there are several intervals which means the different time in the sequence.

MY WORK

MODEL

- for the basic model, we check the reference paper, and construct a basic RNN model.
- in this model there are three layers
- Mask layer: to complete the time step
- RNN layer: for different model, simple RNN, LSTM and GRU layer is selected
- full-connected Layer:it output to a sigmoid function and decide the output value.

MY WORK

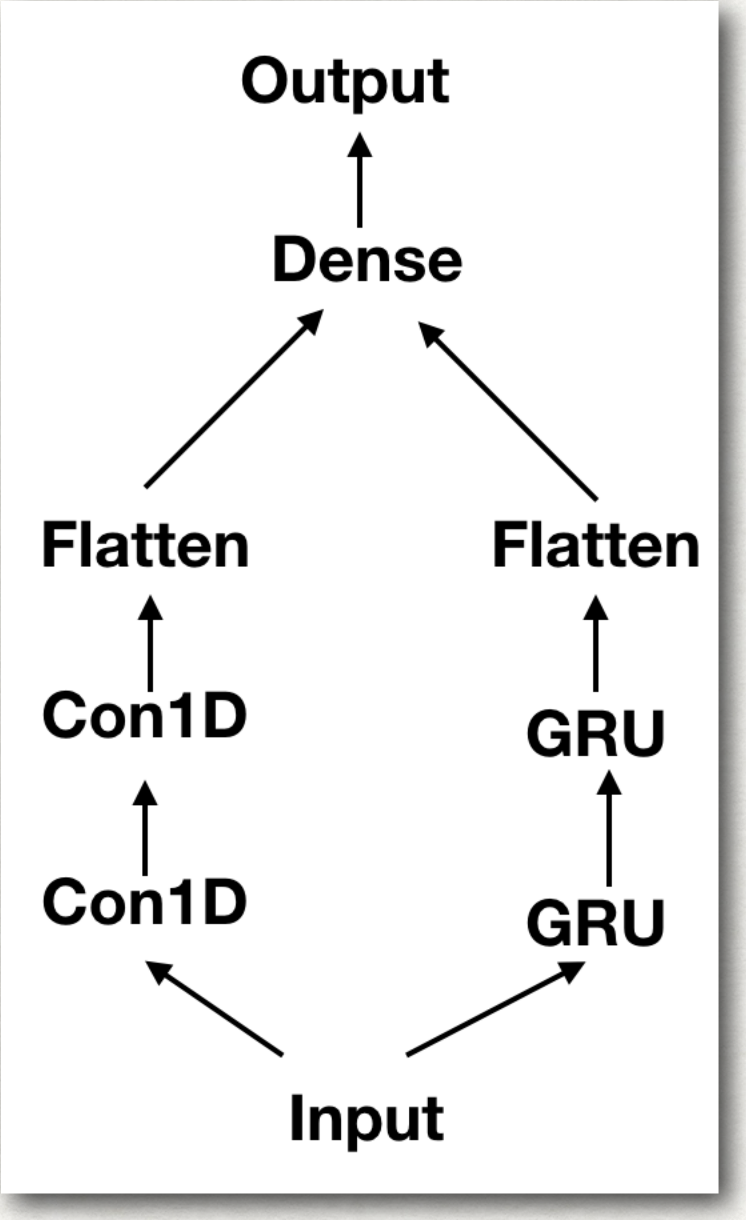
MODEL

- I also some complicated model in which I replace the basic RNN layer with the following layer:
- multiple layer CNN
- CNN with RNN

MY WORK

MODEL

- CNN with RNN



RESULT

Weibo dataset				
Class	Accuracy	Precision	Recall	F_1
tanh-RNN	0.873	0.816	0.964	0.884
LSTM	0.896	0.846	0.968	0.913
GRU	0.908	0.871	0.958	0.913

TABLE 1. REFERENCE RESULT IN WEIBO DATASET

Weibo dataset				
Class	Accuracy	Precision	Recall	F_1
tanh-RNN	0.745	0.740	0.732	0.736
LSTM	0.781	0.769	0.802	0.776
GRU	0.811	0.802	0.816	0.802
CNN-RNN	0.824	0.817	0.830	0.814

TABLE 2. OUR RESULT IN WEIBO DATASET

DATA ANALYSIS

- For the three RNN-based models, for GRU and LSTM remember more long-term information. GRU and LSTM perform well; GRU is slightly better. Compared to RNNbased model, the CNN-combined model has a slightly better performance.However, the overall performance is still lower than the performance in the reference paper.

- Thanks