Tree LSTMs with Convolution Units to Predict Stance and Rumor Veracity in Social Media Conversations

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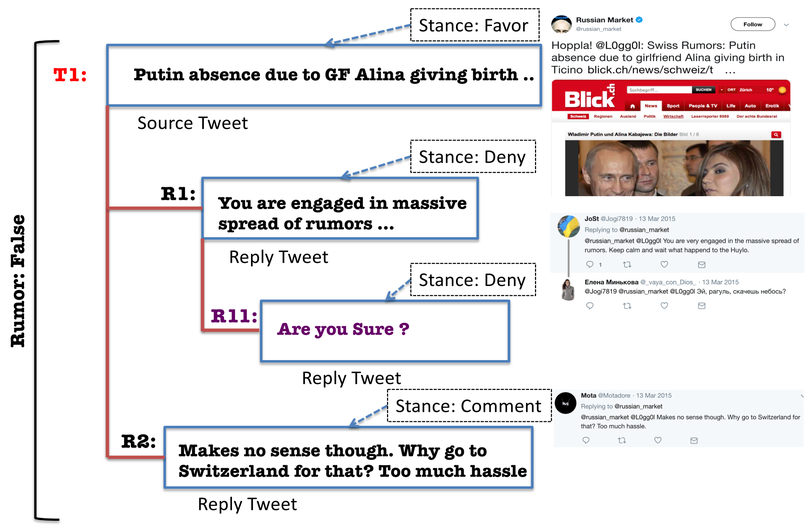
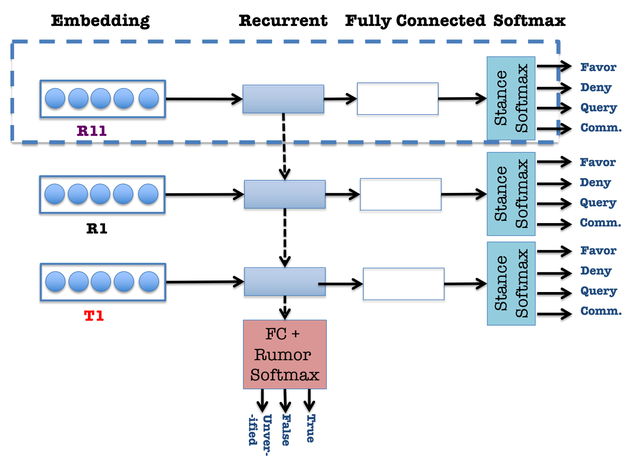
Introduction and Problem Statement

- Identifying groups and their stances (view on an issue) is critical for understanding the spread of information as is the detection of rumors.
- Machine learning on semantic and social networks can help classify stances and rumors automatically.
- On non-tree social media data, LSTMs are commonly used.
- For social media we need different methods. We developed:
  1) Branch LSTM 2) Tree LSTM 3) Binarized Tree LSTM
- Our Tree based models are faster and more accurate.



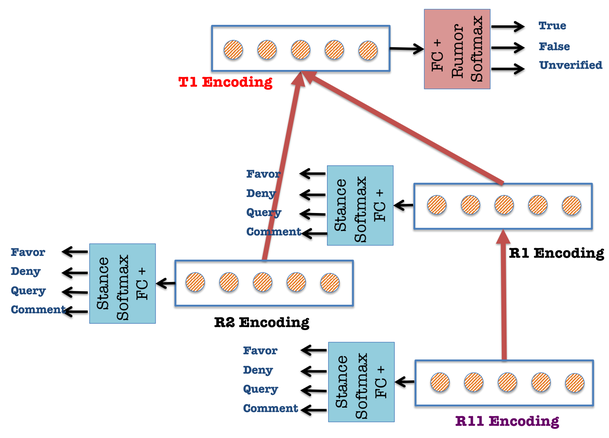
A Social Media Conversation Tree

Machine Learning Models to Classify Stance and Rumor



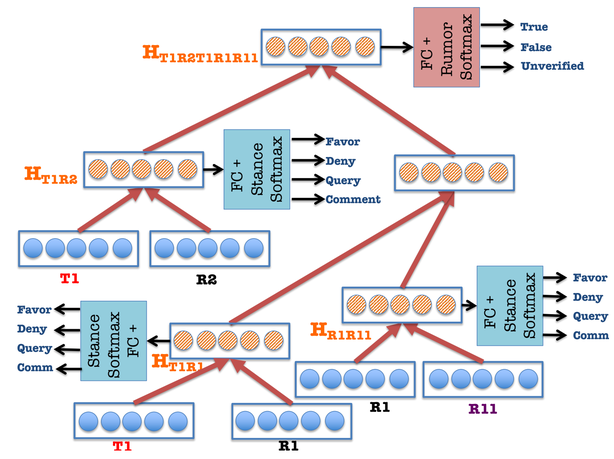
Branch LSTM Model

In branch LSTM, the encodings of source-tweet text and the replies text along a tree branch are used as the input and the stance-labels and rumor-labels are used as the output.



Tree LSTM Model

Tree LSTM is similar to the Branch LSTM except the entire tree conversation is used as input, and to merge information from children, Sum/Convolve+MaxPool operations are used.



Binarized Constituency Tree (BCTree) LSTM Model

BCTree LSTM is similar to Tree LSTM except the original tree is binarized which allows new ways to combine the information from the children e.g. Sum/Convolve/Concat operation.

Results and Discussion

Events	True	False	Unverified
Charlie Hebdo (CH)	193	116	149
Sydney siege (SS)	382	86	54
Ferguson (FG)	10	8	266
Ottawa shooting (OS)	329	72	69
Germanwings-crash (GC)	94	111	33

Table 1. Dataset: Conversation threads and the rumor type labels in the Pheme Rumor Dataset

CellType ↓ Feature →	SKP	EMT	BERT
Branch LSTM Multitask			
	0.358	0.359	0.347
Tree LSTM Multitask			
Sum	0.367	0.356	0.356
Convolve + MaxPooling	0.378	**0.362**	0.366
BCTree LSTM Multitask			
Sum	0.372	0.351	0.366
Concat	0.379	0.361	0.371
Convolve	0.367	0.348	0.359
Sum + Concat	0.381	0.347	0.374
Concat + Convolve	0.370	0.345	0.374
Sum + Convolve	**0.383**	0.346	**0.379**
Sum + Convolve + Concat	0.377	0.342	0.356
Baselines and Prior Research			
(Kochkina et al., 2018)	0.329		
NileTMRG (Enayet and El-Beltagy, 2017)	0.339		
Majority	0.223		

Table 2. Results and Comparison. Higher is better

Conclusions:

- Using the whole conversation tree improves our ability to automatically classify rumor and stance
- Our best Tree models classify the Pheme dataset better than previous work by 11% for rumors and 14% for stances.
- We can use the Tree based in a batch which are much faster to execute.
- Next, we would like to include algorithm based fact-checking in our models .

References:

SKP: Kiros, Ryan, et al. "Skip-thought vectors." Advances in neural information processing systems. 2015.
EMT: Felbo, Bjarke, et al. "Using millions of emoji occurrences to learn any-domain representations for detecting sentiment, emotion and sarcasm."
BERT: Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805 (2018).
Pheme: Zubiaga, Arkaitz, et al. "Towards detecting rumours in social media." *Workshops at the Twenty-Ninth AAAI Conference on Artificial Intelligence*. 2015.

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