Context Helps Determine Spatial Knowledge from Tweets

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Motivations

- Spatial information plays an important role in many applications, such as transportation planning and emergency management systems.
- Most previous work on spatial information with social media are on named entity recognition/disambiguation and location prediction.
- Location prediction, whose goal is to assign a location to a user, targets home location or real-time location.
- Contextual information has been proven in many tasks, such as hate speech detection and sentiment analysis. It can be user information, conversation, or history tweets.
- We are the first to tackle the problem of real-time location prediction with tweets, along with user's history tweets.

Background

- AMT (Amazon Mechanical Turk) is a platform for annotation collection that allows people to publish and complete annotation tasks.
- MACE [1] is a tool that is designed to identify which annotators in AMT are trustworthy and predict the correct underlying annotations.
- BERT [2] is a pretrained language encoder, designed to generate a vector to capture the information contained in a sequence of text.
- LSTM [3] is a type of recurrent neural network which can capture long-term dependencies in sequential data.

Objectives

- Construct a dataset of Twitter streams with spatial annotations. A Twitter stream consists of seven tweets posted chronologically.
- Build neural networks to predict the real-time locations of Twitter users using annotated Twitter streams.
- Conduct a qualitative analysis to provide insights into the errors made by the best-performing model.

Methods

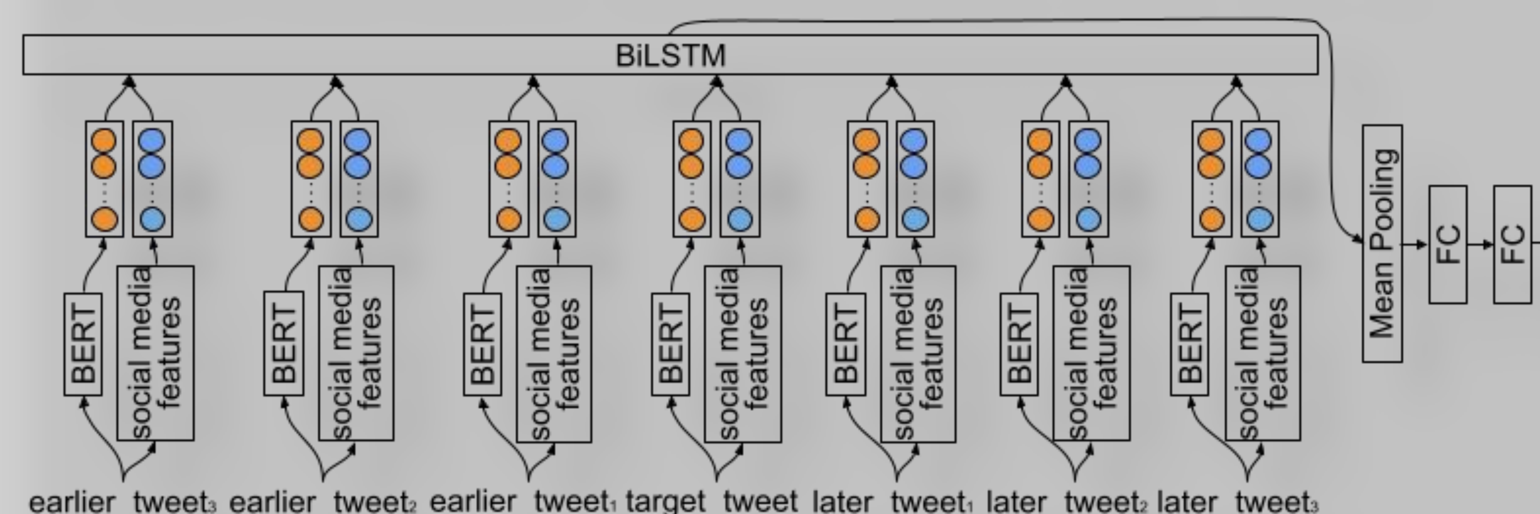
Dataset Creation

Twitter streams → AMT → MACE → Our dataset

- Annotation question: Was the Twitter user at the mentioned location when the tweet was posted?
  - yes: The Twitter user was at the mentioned location.
  - no: I cannot tell if the Twitter user was at the mentioned location.

Context-aware Neural Network

- Social media features: number of hashtags, emojis, URLs, etc.



Results/Discussion

- Our dataset consists of 3,494 Twitter streams. 67.7% of them are annotated yes, and 32.3% are annotated no. Most annotations change depending on if we show annotators the context.

Was the author in *Philadelphia* when t_0 was published? Without context: no; With context: yes

Was the author in *Reno* when t_0 was published? Without context: yes; With context: no

Results/Discussion (Cont.)

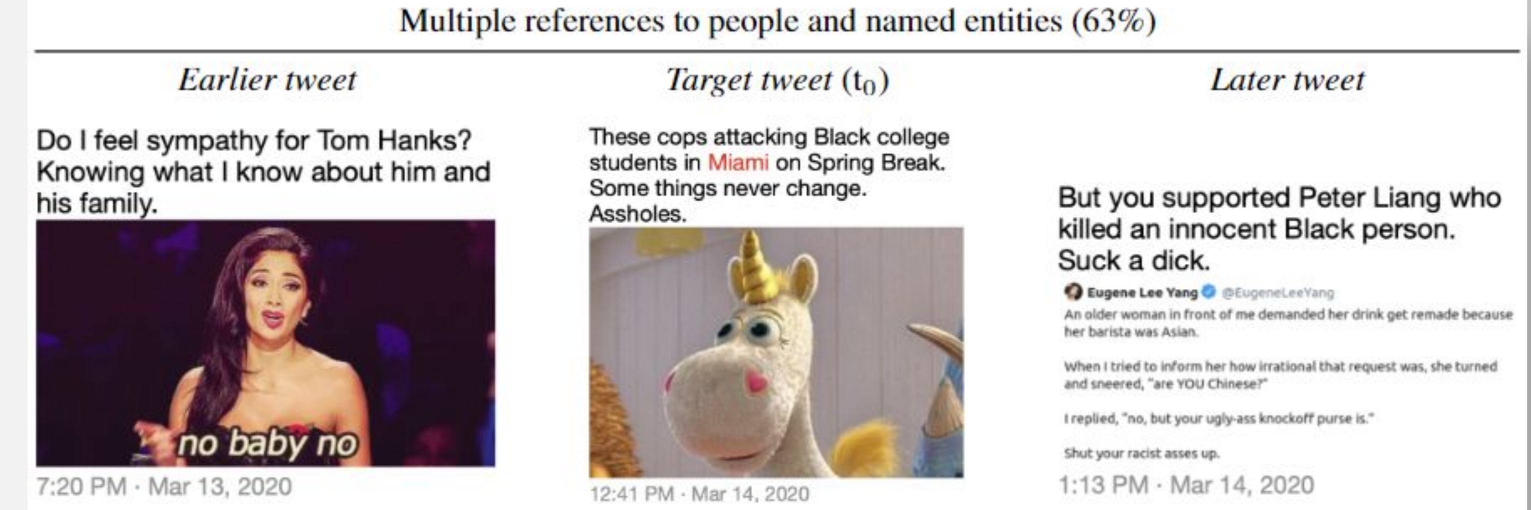
Results with neural networks

	no			yes			Weighted Average		
	P	R	F1	P	R	F1	P	R	F1
Majority baseline	0.00	0.00	0.00	0.68	1.00	0.81	0.46	0.68	0.55
Context-Unaware Network (target tweet)	0.00	0.00	0.00	0.68	1.00	0.81	0.46	0.68	0.55
Context-Aware Networks									
earlier + target tweets	0.00	0.00	0.00	0.68	1.00	0.81	0.46	0.68	0.55
target + later tweets	0.00	0.00	0.00	0.68	1.00	0.81	0.46	0.68	0.55
earlier + target + later tweets	0.44	0.28	0.35	0.71	0.83	0.76	0.62	0.65	**0.63**
without social media features	0.39	0.30	0.34	0.70	0.78	0.74	0.60	0.62	0.61

Most common context-related errors

- Multiple named entities (e.g., Tom Hanks, Peter Liang) mislead the model.
- Lack of timestamps misleads the model.
  - Moving among Denver, San Diego, and Bahamas takes more than 5 hours (10:39 AM - 2:54 PM).

Multiple references to people and named entities (63%)



Was the author in *Miami* when t_0 was published? Ground Truth: no; Predicted: yes

Tweet timestamps are key (21%)

Was the author in *San Diego* when t_0 was published? Ground Truth: no; Predicted: yes

References

1. Hovy et al., Learning Whom to Trust with MACE (2013).
2. Devlin et al., BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding (2019).
3. Sepp Hochreiter and Jürgen Schmidhuber, Long Short-Term Memory (1997).