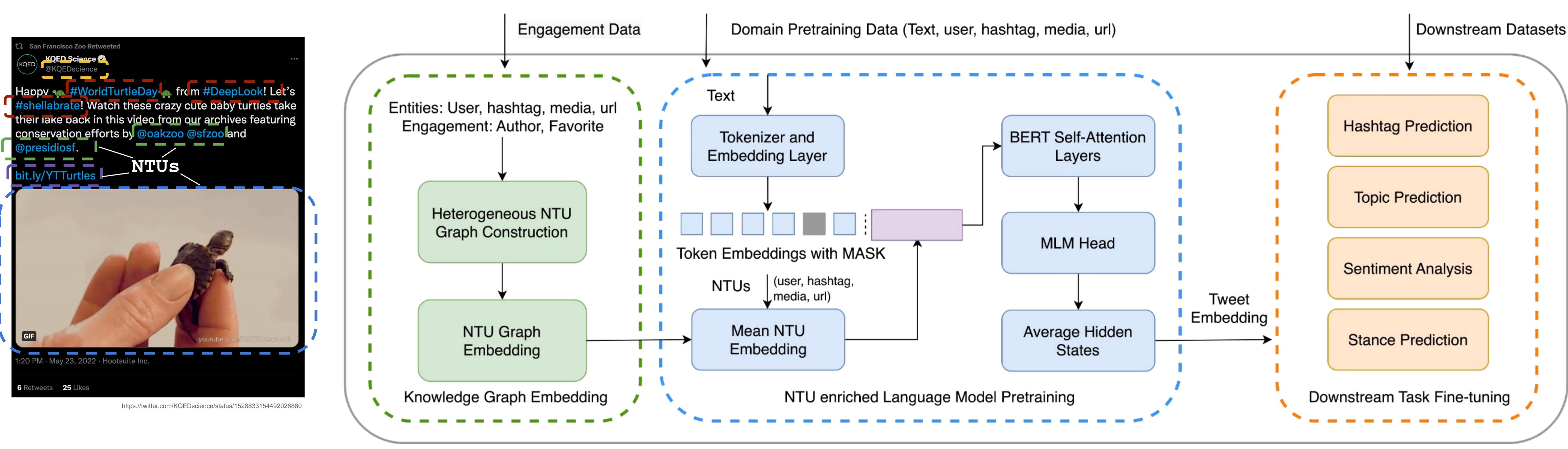
Jinning Li<sup>1</sup>^\*, Shubhanshu Mishra<sup>2</sup>^, Ahmed El-Kishky<sup>2</sup>, Sneha Mehta<sup>2</sup>, Vivek Kulkarni<sup>2</sup> 2022 The 8th Workshop on Noisy User-generated Text (W-NUT)

**Non-Textual Units (NTUs)** are the social contexts which appear alongside a social media post, e.g. *Hashtag*, URL, author, user mentions and *media* 

[happy, [UNK], #, world, ##tur, ##tled, ##ay, [UNK], from, **#, deep, ##10, ##ok**, !, let, , s, **#,** shell, ##ab, ##rate, !, watch, these, crazy, cute, baby, turtles, take, their, lake, back, in, this, video, from, our, archives, featuring, conservation, efforts, by, Q, oak, ##zoo, Q, sf, !##zoo, and, @, pre, ##si, ##dio, ##sf, ., http, :, /, /, bit, ., l, ##y, /, y, ##tt, ##urt, ##les] + [@KQEDscience, #WorldTurtleDay, #DeepLook, #shellabrate, @oakzoo, @sfzoo, @presidiosf, bit.ly/YTTurtles, Media 1]



# Knowledge Graph Embedding

- Graph nodes: author, Hashtag
- Graph edges: connect user-Hashtag if user authors, favorites, or is co-mentioned with a Hashtag
- **Training**: TwHIN framework (El-Kishky et al)

Author: *user*1 **Tweet**: Our paper was accepted at **@WNUT** with @user2 @user3 #nlproc #socialmedia Favorited by: *user*4, *user*5

Table 1: Example tweet with engagement data of author, mentions, Hashtags, and favorites

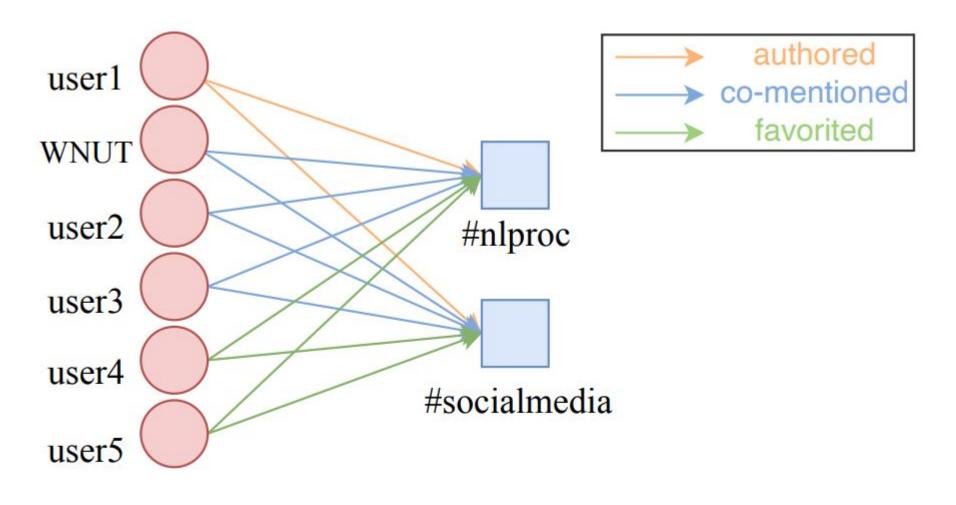


Figure 2: Graph construction with the example data in Table 1 for training NTULM user-Hashtag embeddings.

# **Experiments - Dataset**

NTU heterogeneous network: Tweets (2018-01-01~2022-07-01) with Hashtags and their engagements with users, consisting of 60M Hashtags, 255M users, 5B authorship edges, 3B favorite edges, and 0.9B co-mention edges. We only considered users with 10 - 100 unique Hashtags interactions

MLM fine tuning: 1M Tweets sampled from

(2022-06-01~2022-06-15).

We also fine-tune BERT without NTUs on these Tweets.

**Downstream Tasks**: TweetEval, SemEval, SocialMedialE, Hashtag Pred, Topic

# NTULM: Enriching Social Media Text Representations with Non-Textual Units <sup>1</sup>University of Illinois at Urbana-Champaign, <sup>2</sup>Twitter, Inc., <sup>^</sup>Equal Contribution, \*Work done during internship at Twitter, Inc.

# Results

Model	NTUs	Perplexity	Topic	TweetEval	SemEval 1	SemEval 2	Hashtag	SMIE
		bits	MAP	mean F1	mean F1	mean F1	Recall@10	mean F1
BERT		4.425	0.327	0.577	0.527	0.515	0.689	0.548
NTULM	author	4.412	0.325	0.579	0.527	0.548	0.693	0.548
NTULM	Hashtag	4.391	0.339	0.586	0.534	0.545	0.711	0.539
NTULM a	uthor+Hashtag	4.344	0.343	0.590	0.534	0.545	0.720	0.549

# Why is NTULM effective?

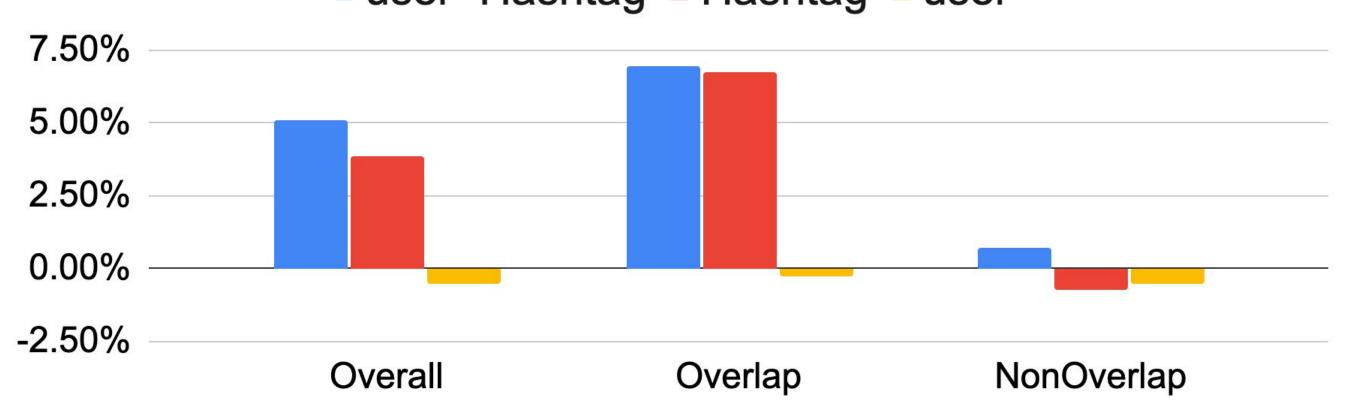
#### Hypothesis:

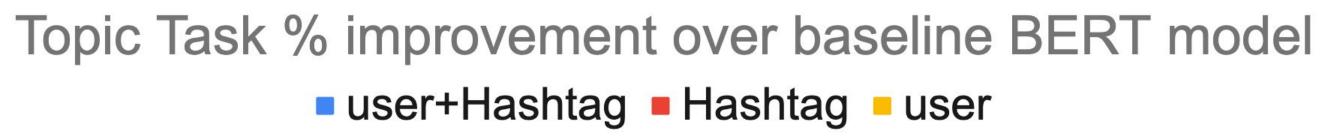
- If NTU is available, NTULM should help.
- If NTU is absent, NTULM should be similar to BERT.

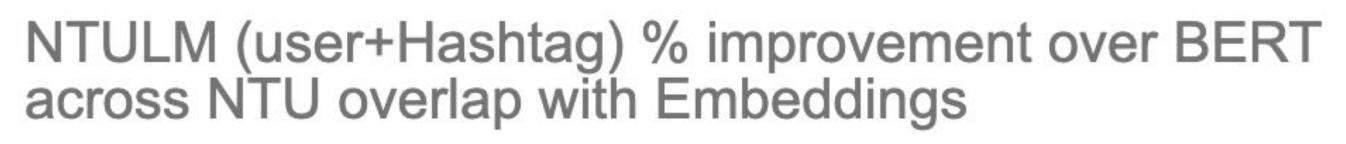
### **Observation:**

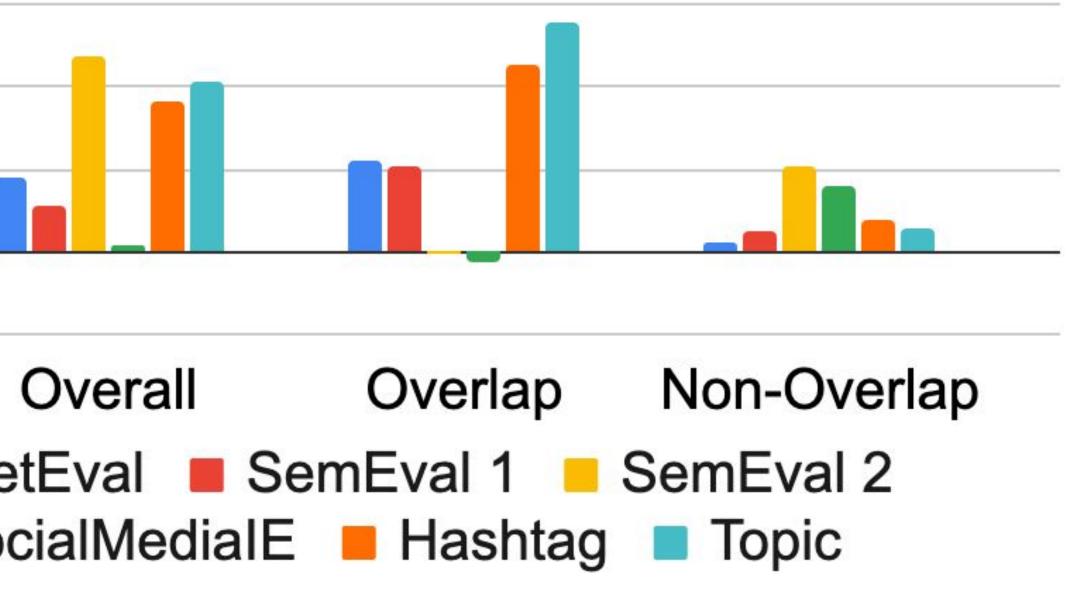
- Hypothesis holds
- Gains with Hashtag NTU are much better than user.

			across NTU ov
Dataset	Hashtag overlap	User overlap	7.50%
Hashtag	99%	10%	5.00%
SemEval	92%	21%	2.50%
Social Media IE	95%	22%	0.00%
Topic	99%	14%	-2.50%
TweetEval	98%	0%	(
Grand Total	95%	14%	Tweet









# **Comparison with BERT Post Concat**

Dataset	Ov	erall	Ove	erlap	Non-Overlap	
	NTULM	BERTC	NTULM	BERTC	NTULM	BERTC
TweetEval	2.27%	-0.80%	2.73%	-3.33%	0.31%	0.65%
SemEval 1	1.36%	0.08%	2.59%	0.21%	0.65%	0.02%
SemEval 2	5.93%	0.22%	-0.07%	0.58%	2.62%	0.07%
SocialMediaIE	0.20%	-2.12%	-0.27%	-4.12%	1.98%	-22.22%
Hashtag	4.51%	4.87%	5.61%	7.46%	1.01%	-3.37%
Topic	5.10%	18.72%	6.92%	34.72%	0.71%	-4.17%

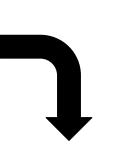
- **NTULM** integrates contexts embedding before attention layer, enabling the BERT encoder to automatically learn the attention of context embeddings.
- **BERTC** directly attach the context embedding after encoder, making it over-dependent on context embedding (affects the language model itself)

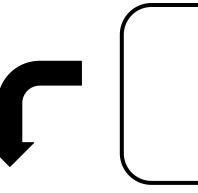
## Conclusion

Jinning Li, Shubhanshu Mishra, Ahmed El-Kishky, Sneha Mehta, and Vivek Kulkarni. 2022. NTULM: Enriching Social Media Text Representations with Non-Textual Units. In Proceedings of the Eighth Workshop on Noisy User-generated Text (W-NUT 2022), pages 69–82, Gyeongju, Republic of Korea. Association for Computational Linguistics.

# **Evaluation on Downstream Tasks**

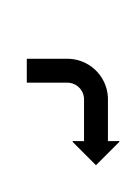
Tweet embedding = average final layer hidden states of valid tokens (and NTUs)



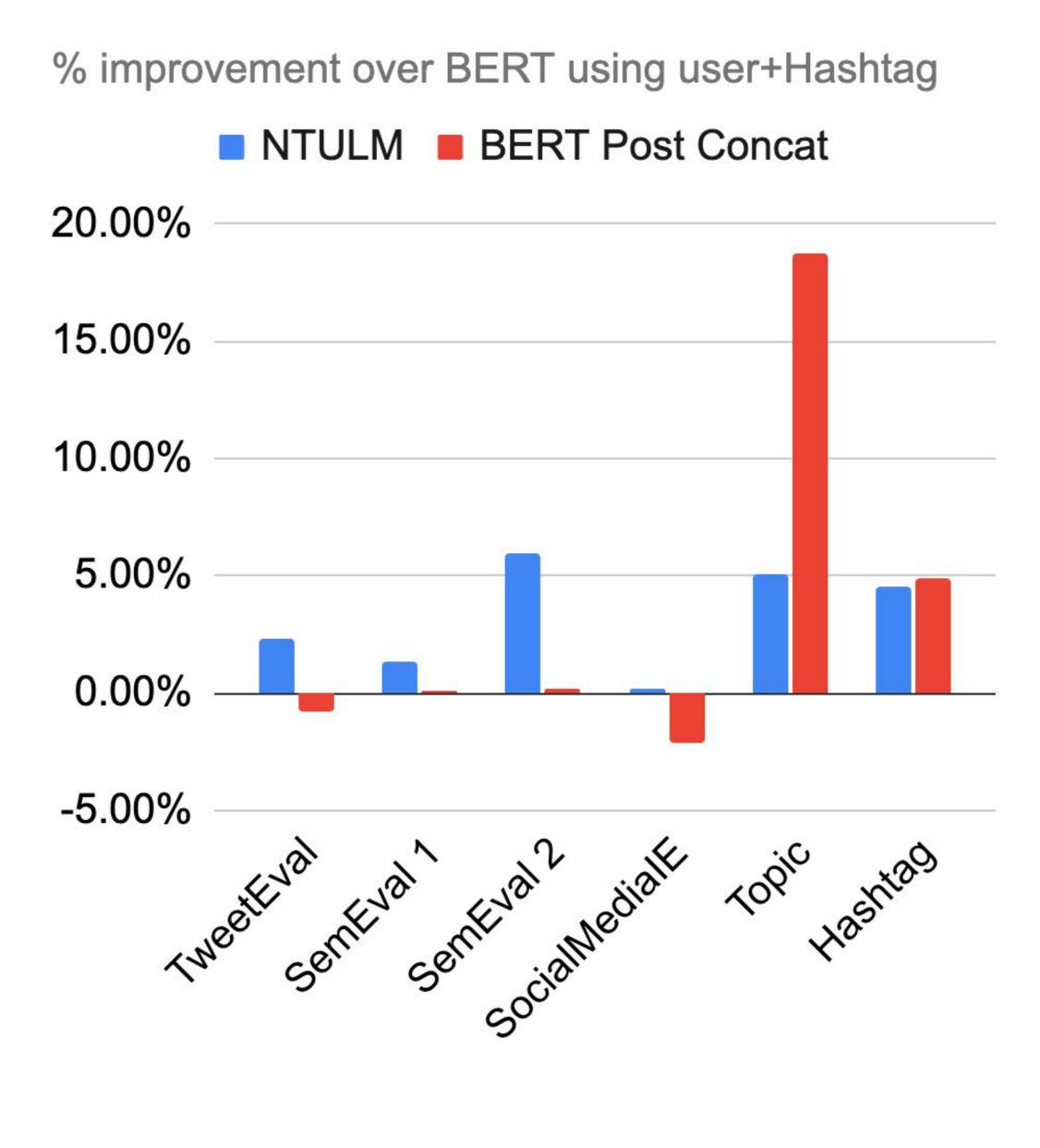


Compute all the Tweet embeddings in Downstream Train and Test sets

Train a 2-Layer MLP classifier for downstream tasks using Tweet embeddings



Evaluate using task specific metrics (F1 score, precision, AUC)



 NTULM shows how to integrate social context of Non Textual Units into language models NTULM led to significant improvements on a variety of tasks over other baselines Improving coverage of NTUs may further improve NTULM.