

Table 2: Twitter user geolocation prediction performance.

	GEOTEXT			TWITTER-US			TWITTER-WORLD		
	Acc@161 ↑	Mean ↓	Median ↓	Acc@161 ↑	Mean ↓	Median ↓	Acc@161 ↑	Mean ↓	Median ↓
MLP + k-d tree	38%	844	389	54%	554	120	34%	1456	415
GCN-LP	58%	576	56	53%	653	126	45%	2357	279
MENET	62%	532	32	66%	433	45	53%	1044	118
MLP-TXT+NET	58%	554	58	66%	420	56	58%	1030	53
GCN	60%	546	45	62%	485	71	54%	1130	108
HLPNN	-	-	-	71%	362	32	59%	828	60
HUG	64%	516	30	72%	359	31	62%	818	49

Table 3: Ablation study on TWITTER-US.

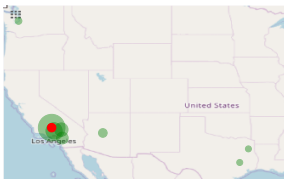
	Acc@161 ↑	Mean ↓	Median ↓
HUG	72%	359	31
w/o graph attention	51%	531	57
w/o language attention	58%	612	63
w/o location regularization	59%	562	51

I just found out I'm doin 2 shows tonite in **Louisville** becuz the 1st show sold out thats lol sorry I just saw your screen name and seen the area code! My bad for bothering u. lol so why gon' be in **Louisville** tonight that's gon' be funny man! yeah well r spr break actually start the 13 but we dnt leave til the 17th so I'll omg they got me weak everything they keep sayin and doin is sooo hilarious

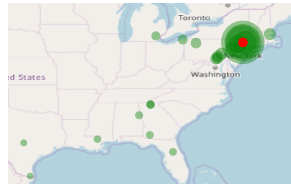
(a) User A

I can't wait to move bck to **LA** thanks i did that one a few hours ago i havent had no sleep but there stil more Why is everyone moving to **culver city** ugh I wanna move to **west hollywood** nxt omg 2mc Live today like its the last don't worry about thee future n don't dwell in the past just **USC** gon cost me \$42,000 smshyht there prices went down it use to be 55,000

(b) User B



(c) User C



(d) User D

Figure 2: Attention weight analysis. (a)-(b) Documents of users A and B. (c)-(d) Geolocations and attention weights of users C and D with their one-hop neighbors.

In Table 3, each module contributes to the performance improvement and the proposed HUG benefits from the combination and the hybrid attention mechanism.

We further investigate the interpretability of the proposed HUG. Figure 2 shows the text and graph examples from the GEOTEXT dataset. In (a) and (b), we show the social media posts of two users (A, B), whose hybrid attention weights for texts are $\alpha_v = 0.643$ and 0.794 , respectively. The blue blocks denote the tweet-level attention weights. The orange denotes the word attention weights and our model can select the words with a strong indication of geolocations like *Louisville*, *LA*, *USC* and *West Hollywood*. Figure 2 (c) and (d) demonstrate two users (C, D) with the geolocations and attention weights of their one-hop neighbors. The hybrid attention weights for graph vector are $\alpha_u = 0.844$ and 0.942 for user C and D, respectively. We plot the geolocations of user C and D in red dots. The green dots are the geolocations of the one-hop neighbors and the dot sizes denote the attention weights. Our proposed HUG also works in terms of the graph attention and location-based regularization, by assigning the higher weights to closer neighbors and lower weights to farther neighbors.

4 CONCLUSION

In this paper, we propose a novel end-to-end framework, Hybrid-attentive User Geolocation (HUG), to jointly model the post texts

and user interactions in social media and predict user geolocations. We introduce the hybrid attention mechanism to automatically determine the importance of texts and social networks while social media posts and interactions are modeled by a graph attention network and a language attention network. The experimental study on three benchmark geolocation datasets from Twitter shows that HUG consistently renders superior prediction performance against baseline approaches. We also demonstrate the interpretability of HUG with in-depth analysis of attention weights.

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