PREDICTING TWEET ENGAGEMENT WITH GRAPH NEURAL NETWORKS

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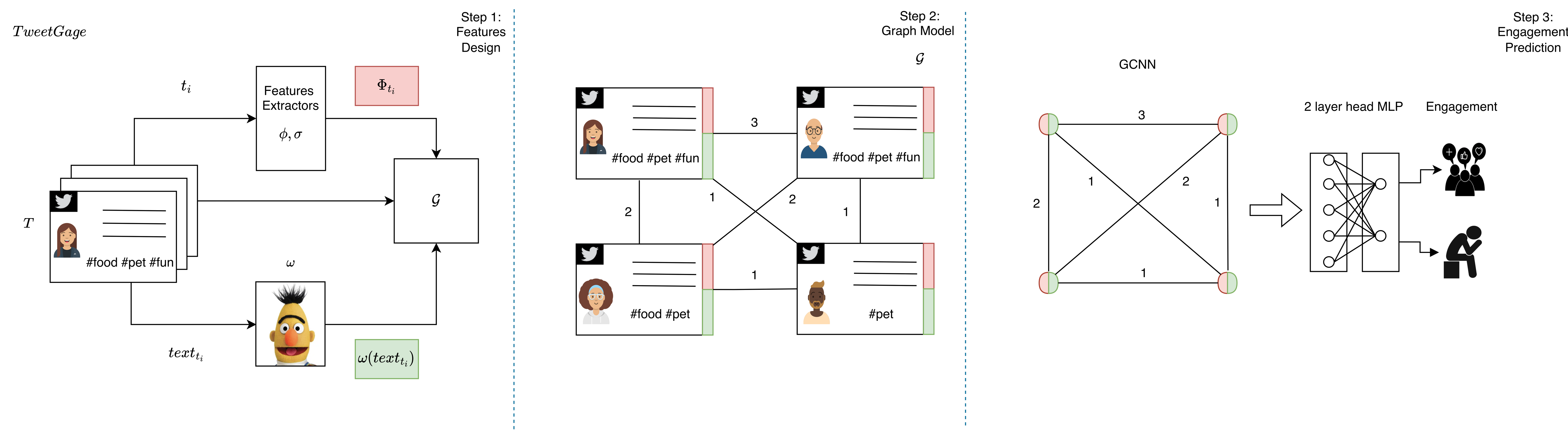
Figure 1: Workflow of *TweetGage*



Abstract

In Social Networks, predicting whether a post will have any impact in terms of engagement is of crucial importance to drive the profitable exploitation of these media. In this paper, we argue that the rise of engagement is also related to another key component, which is the semantic connection among posts published by users in social media. Hence, we propose *TweetGage*, a Graph Neural Network solution to predict user engagement based on a novel graph-based model that represents the relationships among posts.

Methodology

Let T be a set of Twitter posts, where $t_i \in T$ is a tweet, and $\phi(t_i)$ is a function that extracts information about t_i, such as timestamp, text, favorite count, and so on. In order to process $text_{t_i}$, we introduce a function $\omega(text_{t_i})$ as the embedding of $text_{t_i}$, which could be a Word2Vec, GloVe, or BERT. Moreover, we define a function $\sigma(u_{t_i})$ that extracts information about a user u_{t_i} posting the tweet t_i, such as the number of followers and following, the number of tweets, and so on.

Let $\mathcal{G} = \langle T, E_\delta \rangle$ be a network of tweets. Here, the set of edges is represented by E_δ, where there is an edge $e_{ij} = (t_i, t_j, w_{ij})$ if the tweet t_i and t_j share at least one common hashtag and if they were published within a specific time interval δ. The weight w_{ij} is equal to the number of common hashtags between t_i and t_j. Formally speaking, the set of edges is defined as $E_\delta = \{\langle t_i, t_j, |h_{t_i} \cap h_{t_j}|\rangle \ s.t.\ t_i, t_j \in T, h_{t_i} \cap h_{t_j} \neq \emptyset, |\tau_{t_i} - \tau_{t_j}| < \delta\}$.

In our model, δ represents a threshold to control the number of edges between the nodes in $\mathcal{G}$. We can assume that δ narrows down the topics discussed in tweets and connects them in a smarter way. According to the literature, the lifespan of a tweet is between 10 and 30 minutes, therefore we decided to set $\delta = 15$ minutes. We compute the engagement of a tweet t_i as follows [2]:

$$eng(t_i) = Favorite_{t_i} + Retweet_{t_i} \tag{1}$$

In order to perform binary classification on tweets that did or did not generate engagement, we associate a set of class labels L. Specifically, if $eng(t_i) = 0$ then $l_{t_i} = 0$, otherwise if $eng(t_i) \geq 1$ then l_{t_i}.

Since we modeled the Twitter scenario through a graph $\mathcal{G}$ representing the tweets and their interactions, we decided to use a Graph Convolutional Neural Network to predict the engagement of social posts. Our proposal (called *TweetGage*) was tested on a Twitter dataset, whose statistics are reported in Table 1.

Table 1: Statistics of our dataset

First day	November 1^{st}, 2021
Last day	November 7^{th}, 2021
Number of users	194,046
Number of posts	243,750
Mean number of posts by day	34,821.43
Number of unique hashtags	94,646

Analysis of Centrality Measures

We analyzed the network centralities of the posts in order to verify possible differences between posts with engagement and posts without engagement.

Table 2: Centrality measures statistics and results of Kolmogorov–Smirnov tests split by engagement classes

	l_{t_i}	Mean	Std	K-S test p-value
Weighted Degree Centrality	0	110.63	384.05	< 0.01
	1	39.12	197.26	
Closeness Centrality	0	$1.12\,e^{-3}$	$2.14\,e^{-3}$	< 0.01
	1	$1.06\,e^{-3}$	$2.09\,e^{-3}$	
Betweenness Centrality	0	$3.51\,e^{-6}$	$2.13\,e^{-5}$	< 0.01
	1	$2.28\,e^{-6}$	$1.91\,e^{-5}$	
Eigenvector Centrality	0	$2.38\,e^{-4}$	$1.08\,e^{-3}$	< 0.01
	1	$4.53\,e^{-5}$	$1.10\,e^{-3}$	

Results

TweetGage was evaluated by comparing it to various baseline architectures, including the XGBoost algorithm (the winning solution from the 2020 RecSys Challenge) [1], BERT fine-tuning (BERT FT), MLP, and CNN. A variation of TweetGage was also tested, which used Graph Attention Networks (GAT) with a Multi-Head Attention Layer.

Table 3: Comparison results between TweetGage and state-of-the-art approaches

Architecture	Acc	Prec	Recall	AUC_{ROC}	AUC_{PR}	F1
BERT FT	0.50	0.51	0.50	0.49	0.64	0.50
MLP	0.67	0.67	0.68	0.74	0.74	0.67
CNN	0.70	0.70	0.70	0.77	0.76	0.70
XGBoost[1]	0.72	0.72	0.72	0.80	0.80	0.72
TweetGage(GAT)	0.87	0.87	0.87	0.92	0.90	0.88
TweetGage	**0.89**	**0.89**	**0.89**	**0.95**	**0.94**	**0.89**

Table 4: Ablation study on the importance of the features considered for TweetGage.
* Feature set reduced with PCA

Φ_{t_i}	$\omega(text_{t_i})$	Acc	Prec	Recall	AUC_{ROC}	AUC_{PR}	F1
✗	✗	0.50	0.50	0.25	0.75	0.50	0.33
✓	✗	0.87	0.87	0.88	0.93	0.92	0.87
✗	✓	0.88	0.88	0.88	0.94	0.92	0.88
✗	✓*	0.84	0.85	0.85	0.92	0.89	0.85
✓*	✓*	0.87	0.87	0.88	0.94	0.91	0.87
✓	✓*	0.88	0.88	0.89	0.95	0.94	0.88
✓	✓	**0.89**	**0.89**	**0.89**	**0.95**	**0.94**	**0.89**

Conclusion

In this paper, we proposed a novel approach for binary classification of Twitter posts based on user engagement using Graph Neural Networks. Future research includes extending to multi-class classification and creating a graph model considering users and different edges to enable a recommendation system.

References

[1] V. W. Anelli, A. Delić, G. Sottocornola, J. Smith, N. Andrade, L. Belli, M. Bronstein, A. Gupta, S. Ira Ktena, A. Lung-Yut-Fong, et al. Recsys 2020 challenge workshop: engagement prediction on twitter's home timeline. In *Proceedings of the Recommender Systems Conference (RecSys'20)*, pages 623–627, Online, 2020. ACM.

[2] E. Diaz-Aviles, H. T. Lam, F. Pinelli, S. Braghin, Y. Gkoufas, M. Berlingerio, and F. Calabrese. Predicting user engagement in twitter with collaborative ranking. In *Proceedings of the Recommender Systems Challenge (RecSys'14)*, pages 41–46. ACM, Foster City, California, USA, 2014.