Heterogeneity-aware Twitter Bot Detection with Relational Graph Transformers

Shangbin Feng, Zhaoxuan Tan, Rui Li, Minnan Luo

Motivation

Numerous et al. — Twitter bot detection is an important task!

Yang et al. and others — We propose hand-crafted features.

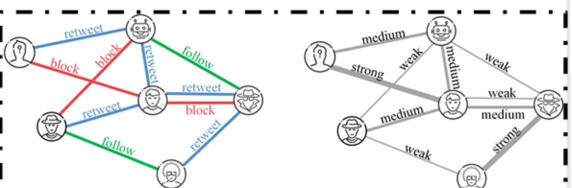
Great, but feature-based approaches could not adapt to bot **evolution**. — Feng et al. CIKM 2021

Kudugunta et al. and others — We use RNN, GAN and other DL techniques.

Great, but individual analysis could not capture novel bot **communities**. — Feng et al. ASONAM 2021

GraphHist and others — How about graph-based approaches?

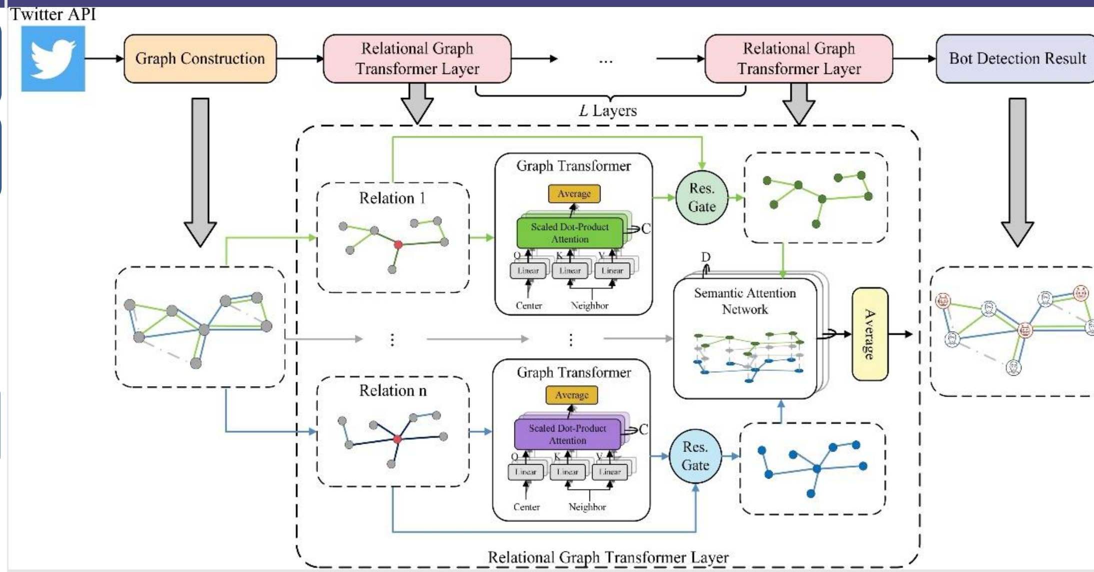
Combining with inherent **Twitter heterogeneities**? — Ours



Relation Heterogeneity

Influence Heterogeneity

Relational Graph Transformers



We propose **relational graph transformers**, a novel GNN architecture, which

- Split HINs into relational sub-graphs, learn relation-specific representations and aggregates with semantic attention networks
- Model relation and influence heterogeneities with relational sub-graphs and graph transformers

Experiments and Results

Table 1: Characteristic and performance of different Twitter bot detection methods. Deep, interactive, representative, graph-based and heterogeneity-aware denotes whether the method involves deep learning, leverages user interactions, learns user representation, involves graph neural networks or leverages Twitter heterogeneity.

Method	Deep	Interactive	Representative	Graph-based	Heterogeneity-aware	Accuracy	F1-score
Lee *et al.*						0.7456	0.7823
Yang *et al.*						0.8191	0.8546
Cresci *et al.*						0.4793	0.1072
Kudugunta *et al.*	✓					0.8174	0.7515
Wei *et al.*	✓					0.7126	0.7533
Miller *et al.*		✓				0.4801	0.6266
Botometer		✓				0.5584	0.4892
SATAR	✓	✓	✓			0.8412	0.8642
Alhosseini *et al.*	✓	✓	✓	✓		0.6813	0.7318
BotRGCN	✓	✓	✓	✓		0.8462	0.8707
Ours	✓	✓	✓	✓	✓	**0.8664**	**0.8821**

Our relational graph transformers outperform feature, DL and graph-based Twitter bot detection baselines on a comprehensive benchmark TwiBot-20.

Table 3: Ablation study of our proposed GNN architecture. RT and SA denote relational transformers and semantic attention networks respectively.

Ablation Settings	Accuracy	F1-score
full model	**0.8664**	**0.8821**
remove transformer in RT	0.8521	0.8679
remove gated residual in RT	0.8478	0.8646
replace RT with GAT	0.8571	0.8726
replace RT with GCN	0.8444	0.8619
replace RT with SAGE	0.8546	0.8687
summation as SA	0.8512	0.8654
mean pooling as SA	0.8512	0.8663
max pooling as SA	0.8495	0.8629
min pooling as SA	0.8555	0.8704

- Ablation study examining relational graph transformers.
- Case study of correlation: botness and heterogeneities.
- Our approach learns great representations for users.

Xi'an Jiaotong University