Heterogeneous Graph Transformer with Poly-Tokenization

Zhiyuan Lu, Yuan Fang, Cheng Yang, Chuan Shi







In the Proceedings of the 33rd International Joint Conference on Artificial Intelligence.

Background

Graph Neural Networks $h_{v}^{l} = M(h_{v}^{l-1}, \{h_{i}^{l-1}: i \in N_{v}\}; \theta^{l})$

Message passing function



- Limited expressive power
- Over-smoothing problem

Graph Transformers Attention(Q, K, V) = softmax $\left(\frac{QK^T}{\sqrt{d_k}}\right)V$ Fully-connected self-attention



- Stronger expressive power
- Alleviate over-smoothing

Background

Heterogeneous Graph

HGs are powerful for representing complex real-world networks (e.g., academic networks, social networks).



Motivation

- 1. Current graph transformer models struggle to integrate the rich and complex semantics inherent in heterogeneous graphs.

 $\equiv p_1$

 $\boxed{\mathbf{T}}_{t_1} \quad \boxed{\mathbf{T}}_{t_2} \quad \boxed{\mathbf{I}}_{t_2} \quad \boxed{\mathbf{I}}_{t_2} \quad \boxed{\mathbf{I}}_{t_3}$

 $\exists p_2$

 $[\exists]_{p_3}$





Feed Forward

Add & Norm Multi-Head

Attention

Input Embedding

Inputs

N×

Positional Encoding

The Overall Framework

The poly-tokenization mechanism



Figure 1: The overall framework of PHGT.

Node Token



Semantic Token



- Sample meta-path instances according to a pre-defined meta-path set.
- Each meta-path instance is converted to a semantic token

The embedding of path instance p_k^i	An instance of meta-path p_k				
$\mathbf{z}_{p_k}^i = \texttt{ReadOut}(\{\mathbf{z}_u \mid u \in p_k^i\})$					
$\mathbf{H}^i_{[t sem]} = [\mathbf{z}^i_{p_1}, \mathbf{z}^i_{p_2}]$	$[\mathbf{z}_{p_2},,\mathbf{z}_{p_N}^i]^ op$				

Global Token

Author (A) Paper (P) Conference (C)



$$\mathbf{H}_{[\texttt{global}]} = [\mathbf{z}_{c_1}, \mathbf{z}_{c_2}, ..., \mathbf{z}_{c_M}]^{ op}$$

Summarize nodes with similar structure

Heterogeneous Node Classification Experiments

Methods	DBLP		IMDB		ACM		Freebase	
1120110005	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1
RGCN	92.07±0.50	91.52±0.50	62.05±0.15	58.85±0.26	91.41±0.75	91.55±0.74	60.82±1.23	59.08±1.44
HAN	92.05±0.62	91.67±0.49	64.63±0.58	57.74±0.96	90.79±0.43	90.89±0.43	61.42±3.56	57.05±2.06
GTN	93.97±0.54	93.52±0.55	65.14±0.45	60.47±0.98	91.20±0.71	91.31±0.70	-	-
HetGNN	92.33±0.41	91.76±0.43	51.16±0.65	48.25±0.67	86.05±0.25	85.91±0.25	62.99±2.31	58.44±1.99
MAGNN	93.76±0.45	93.28±0.51	64.67±1.67	56.49±3.20	90.77±0.65	90.88±0.64	64.43±0.73	58.18±3.87
HGT	93.49±0.25	93.01±0.23	67.20±0.57	63.00±1.19	91.00±0.76	91.12±0.76	66.43±1.88	60.03±2.21
Simple-HGN	94.46±0.22	94.01±0.24	67.36±0.57	63.53±1.36	93.35±0.45	93.42±0.44	67.49±0.97	62.49±1.69
ANS-GT	93.15±0.51	92.75±0.43	66.65±0.35	62.52±0.61	92.55±0.54	93.67±0.62	67.33±0.61	61.24±0.57
NodeFormer	93.68±0.42	93.05±0.38	65.86±0.42	62.15±0.77	91.89±0.31	92.72±0.84	67.01±0.52	60.83±1.41
HINormer	94.94±0.21	94.57±0.23	67.83±0.34	64.65±0.53	93.15±0.36	93.28±0.43	67.78±0.39	62.76±1.10
PHGT	95.33±0.18	94.96±0.17	68.81±0.08	65.91±0.30	93.72±0.40	93.79±0.39	68.74±1.42	61.73±1.86

Ablation and Efficiency Studies

	DBLP	IMDB	ACM	Freebase
w/o both	94.80	68.35	93.34	67.58
w/o semantic token	94.94	68.58	93.41	67.73
w/o global token	94.91	68.54	93.55	68.06
PHGT	95.33	68.81	93.72	68.89



Ablation studies (micro-f1 score)

Memory usage as graph size increases

Conclusion

> PHGT addressed the two limitations of existing graph transformer models:

(1) the inability to capture heterogeneous semantics;

(2) the incapacity to model intricate long-range dependencies.

Through comprehensive experiments on four benchmark datasets, we demonstrate the efficacy of our PHGT approach.



Thanks !

Heterogeneous Graph Transformer with Poly-Tokenization

Zhiyuan Lu, Yuan Fang, Cheng Yang, Chuan Shi