

Dynamic Heterogeneous Graph Attention Neural Architecture Search

RESEARCH CENTER OF ALIGABA ARTIFICIAL INTELLIGENCE GOVERNANCE

阿里巴巴人工智能治理
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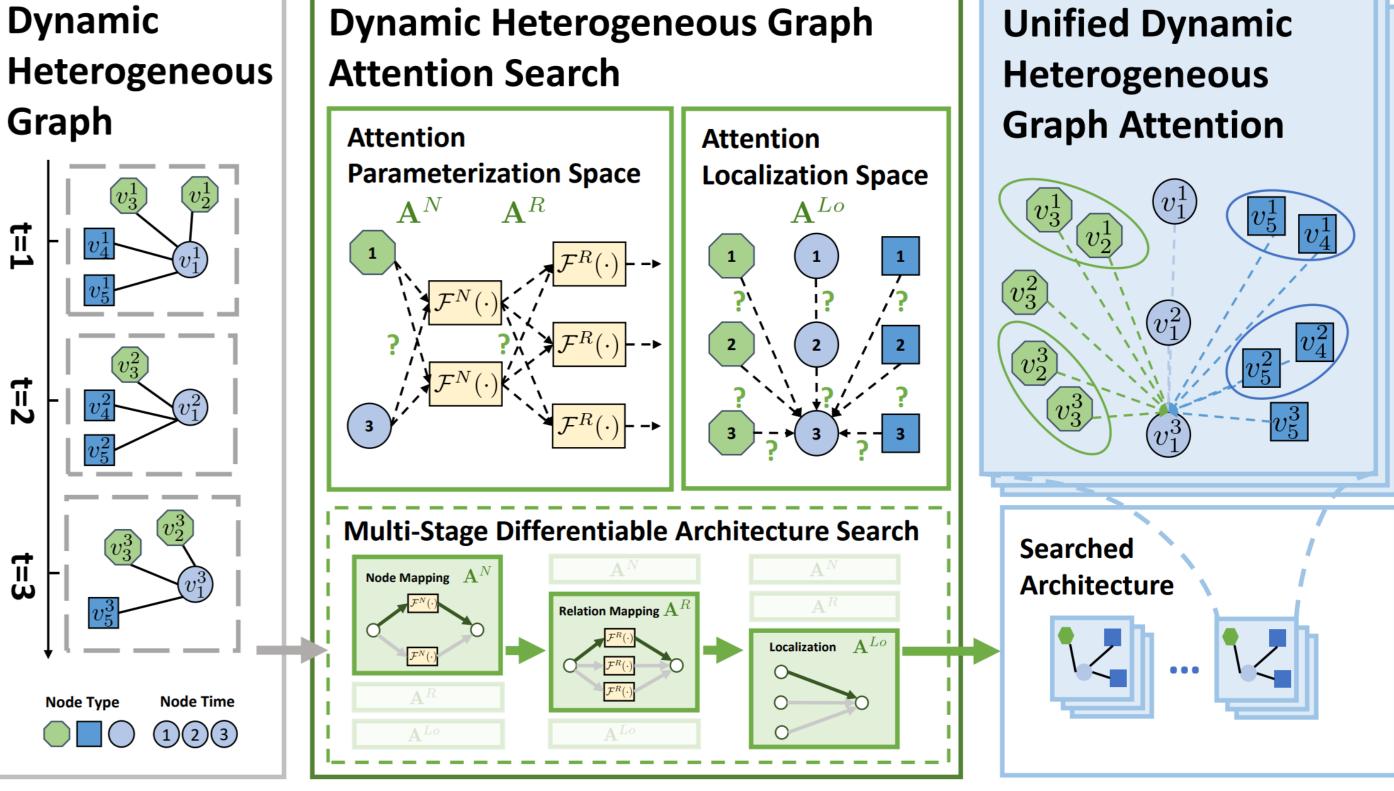
> Motivations

- Dynamic heterogeneous graphs are ubiquitous in real-world
 - Have applications including social networks, e-commerce networks, academic citation networks, etc.
 - Contain richer heterogeneous information represented as node and edge types, and dynamic information like evolving graph structures over time.
- The existing dynamic heterogenous graph neural networks (DHGNNs) are limited due to
 - Manual design require extensive human endeavors
 - Fixed architecture can not adapt to diverse scenarios
 - Tackle heterogeneous and dynamic information separately.
- Our Goal: Automatically tailor an optimal DHGNN architecture and adapt to various dynamic heterogeneous graph scenarios with
 - search space that jointly consider the complex spatial-temporal dependencies and heterogeneous interactions in graphs
 - search algorithm that efficiently search in the potentially large and complex search space for dynamic heterogeneous graphs

> Method

- We propose <u>Dynamic Heterogeneous Graph Attention Neural Architecture</u> Search (DHGAS) to automate DHGNN design with
 - Unified dynamic heterogeneous graph attention to jointly tackle spatio-temporal dependencies while capable of differentiating time/node/edge types
- Localization space to determine where the attention should be applied and parameterization space to determine how the attention should be parameterized.
- Multi-stage differentiable search algorithm to efficiently explore the space and stable the search process

Model (DHGAS)

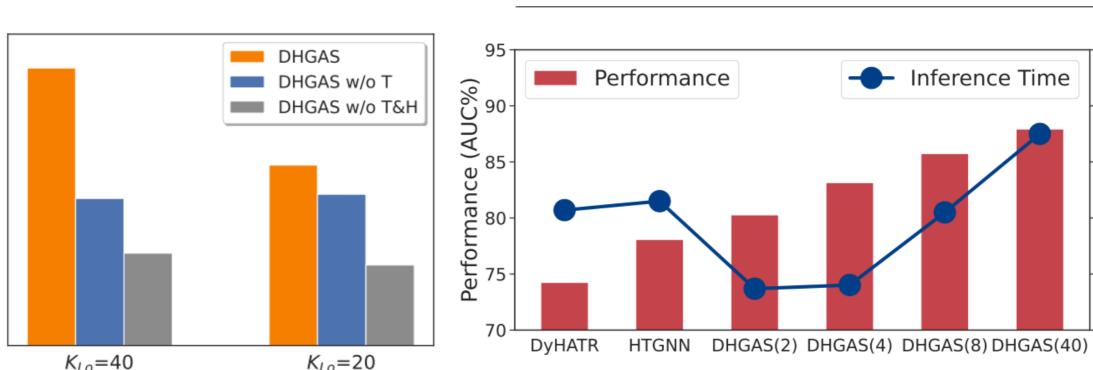


> Experiments

Real world datasets

DHGAS outperforms baselines by
1) jointly tackling dynamic and
heterogeneous information
2) automatically tailoring optimal
DHGNN for various scenarios

Task	Link Prediction		Node Classification		Node Regression
Metric	(AUC%) ↑		(F1%) ↑		$(MAE) \downarrow$
Dataset	Aminer	Ecomm	Yelp	Drugs	COVID-19
GCN	73.84 ± 0.06	77.94 ± 0.22	37.02 ± 0.00	56.43 ± 0.21	846 ± 101
GAT	80.84 ± 0.96	78.49 ± 0.31	35.54 ± 0.00	57.06 ± 0.00	821 ± 91
RGCN	82.75 ± 0.12	82.27 ± 0.51	37.75 ± 0.00	57.97 ± 0.14	833 ± 95
HGT	78.43 ± 1.81	81.09 ± 0.52	34.62 ± 0.00	57.65 ± 0.01	805 ± 88
DyHATR	74.24 ± 2.09	71.69 ± 0.90	34.49 ± 0.16	55.51 ± 0.09	643 ± 36
HGT+	85.60 ± 0.12	76.68 ± 0.85	38.33 ± 0.00	59.09 ± 0.00	-
HTGNN	78.08 ± 0.80	76.78 ± 6.37	36.33 ± 0.07	$\overline{56.24 \pm 0.34}$	555 ± 34
GraphNAS	81.61 ± 0.98	79.37 ± 0.21	37.73 ± 0.00	57.13 ± 0.52	820 ± 43
DiffMG	85.04 ± 0.30	81.69 ± 0.06	38.65 ± 0.00	58.45 ± 0.15	629 ± 63
DHGAS	$\textbf{88.13} \pm \textbf{0.18}$	86.56 ± 0.58	$\overline{\textbf{41.99} \pm \textbf{0.18}}$	62.35 ± 0.03	$\textbf{536} \pm \textbf{43}$



Additional Results

DHGAS can exploit dynamic heterogenous information, permit efficiency tradeoff and automatically discover complex yet competitive DHGNN architectures for various datasets