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StarGAT: Star-Shaped Hierarchical Graph Attentional Network for Heterogeneous Network Representation Learning

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CONTENTS

1 Backgrounds

2 Proposed Model: StarGAT

3 Experiments

4 Conclusions

CONTENTS

1 **Backgrounds**

2 Proposed Model: StarGAT

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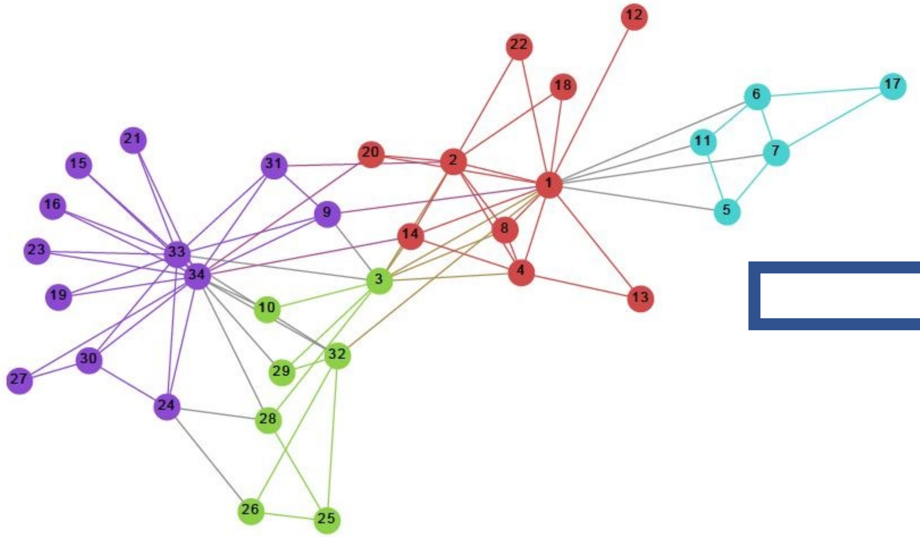
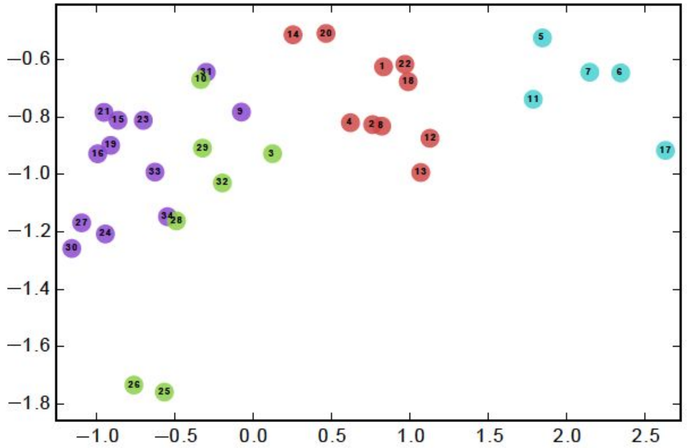
4 Conclusions

1 Backgrounds

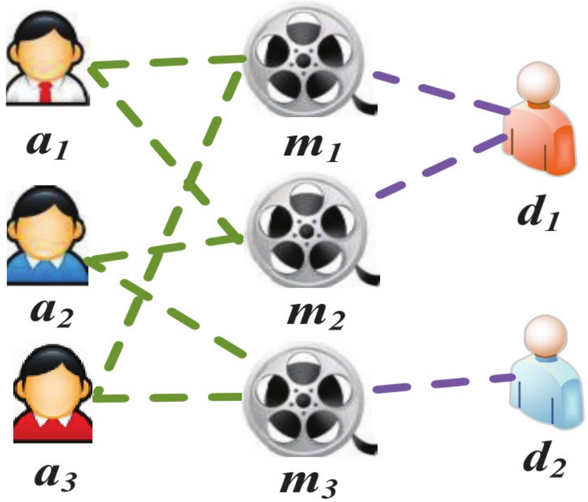
Graph Representation Learning

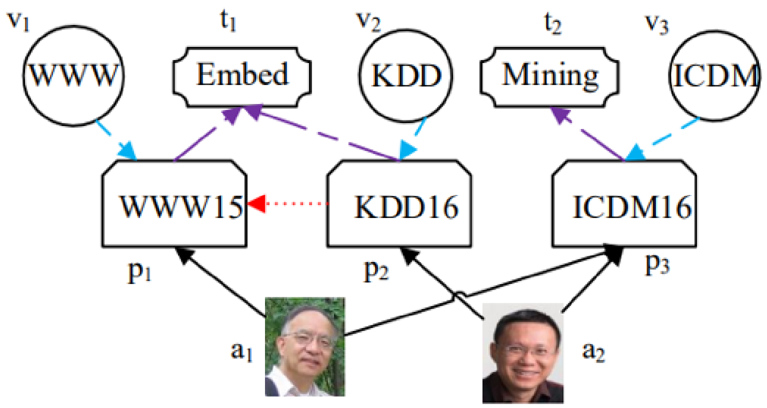


$$\begin{bmatrix} 0.54 & 0.27 \\ 0.22 & 0.91 \\ 0.55 & 0.28 \\ 0.98 & 0.11 \\ 0.32 & 0.87 \\ 0.26 & 0.11 \\ 0.78 & 0.29 \end{bmatrix}$$



- More than one node types and/or more than one link types.





- Rich semantic information.

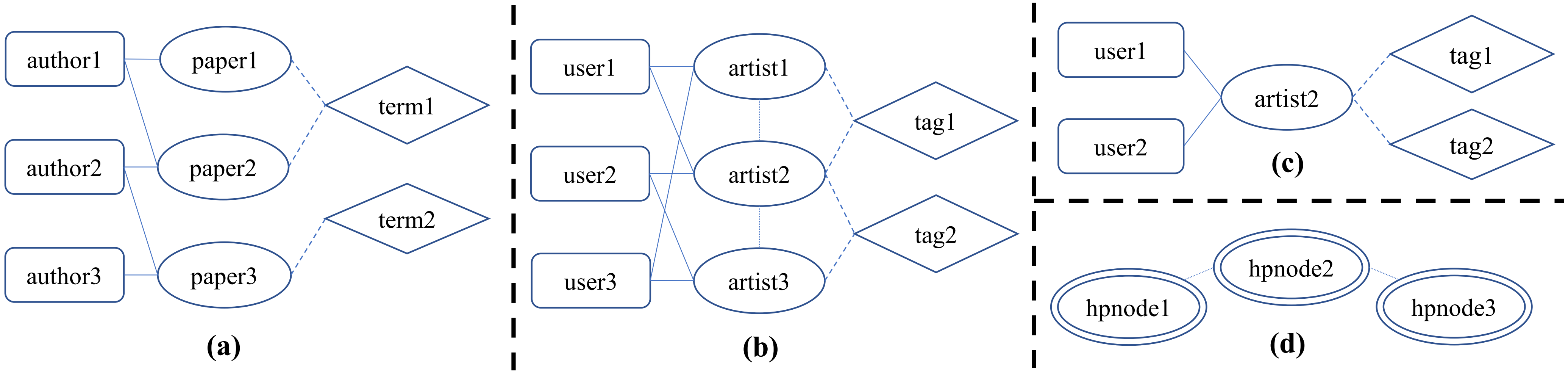
Two movies directed by the same director.

Author1 and author2 are co-authors of the paper.

Existing metapath based HIN representation learning methods:

- Treat different node types in a metapath equally.
- Only consider node-level and metapath-level information aggregation.

Motif: subnetworks appearing frequently in the original network.



CONTENTS

1 Backgrounds

2 **Proposed Model: StarGAT**

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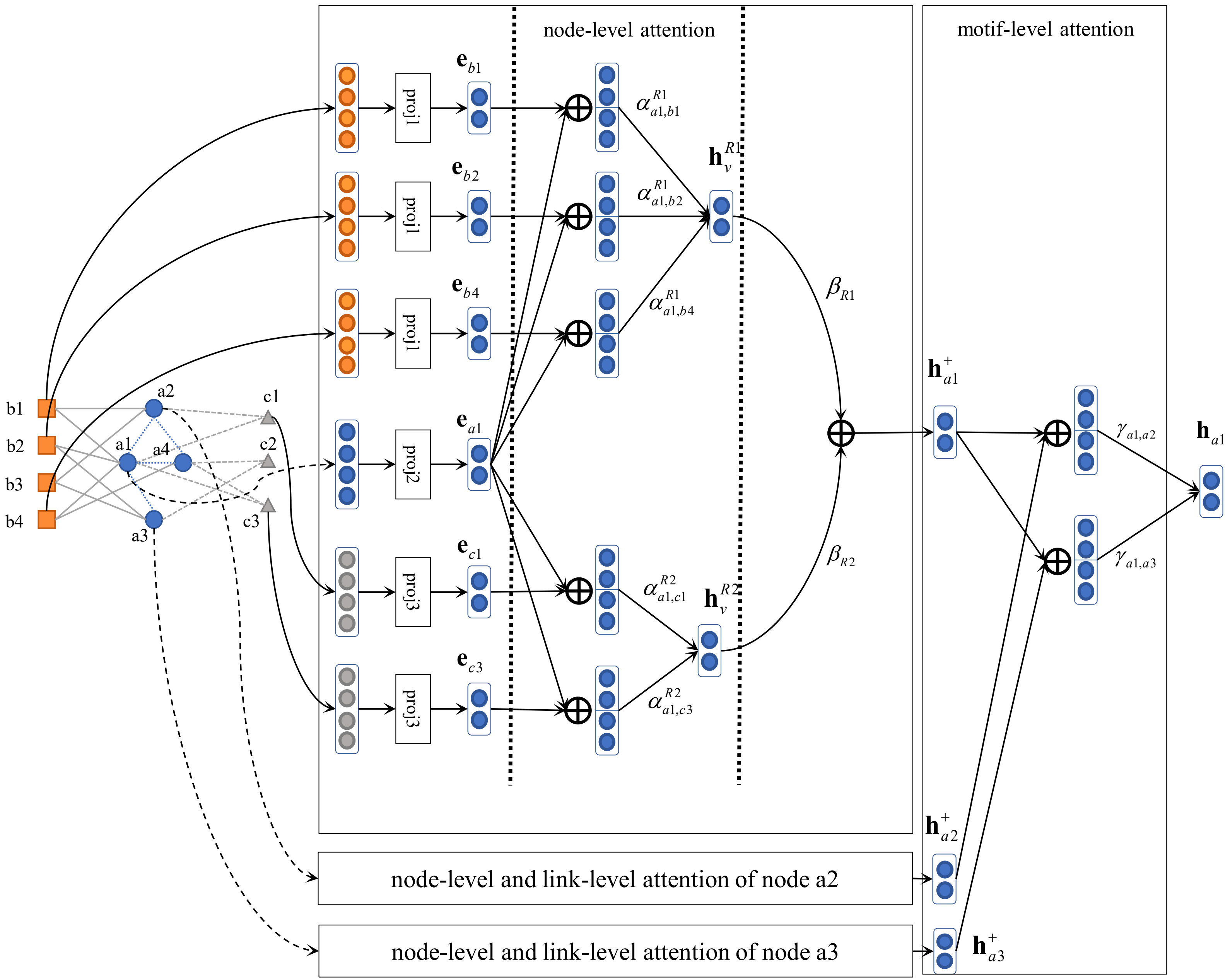
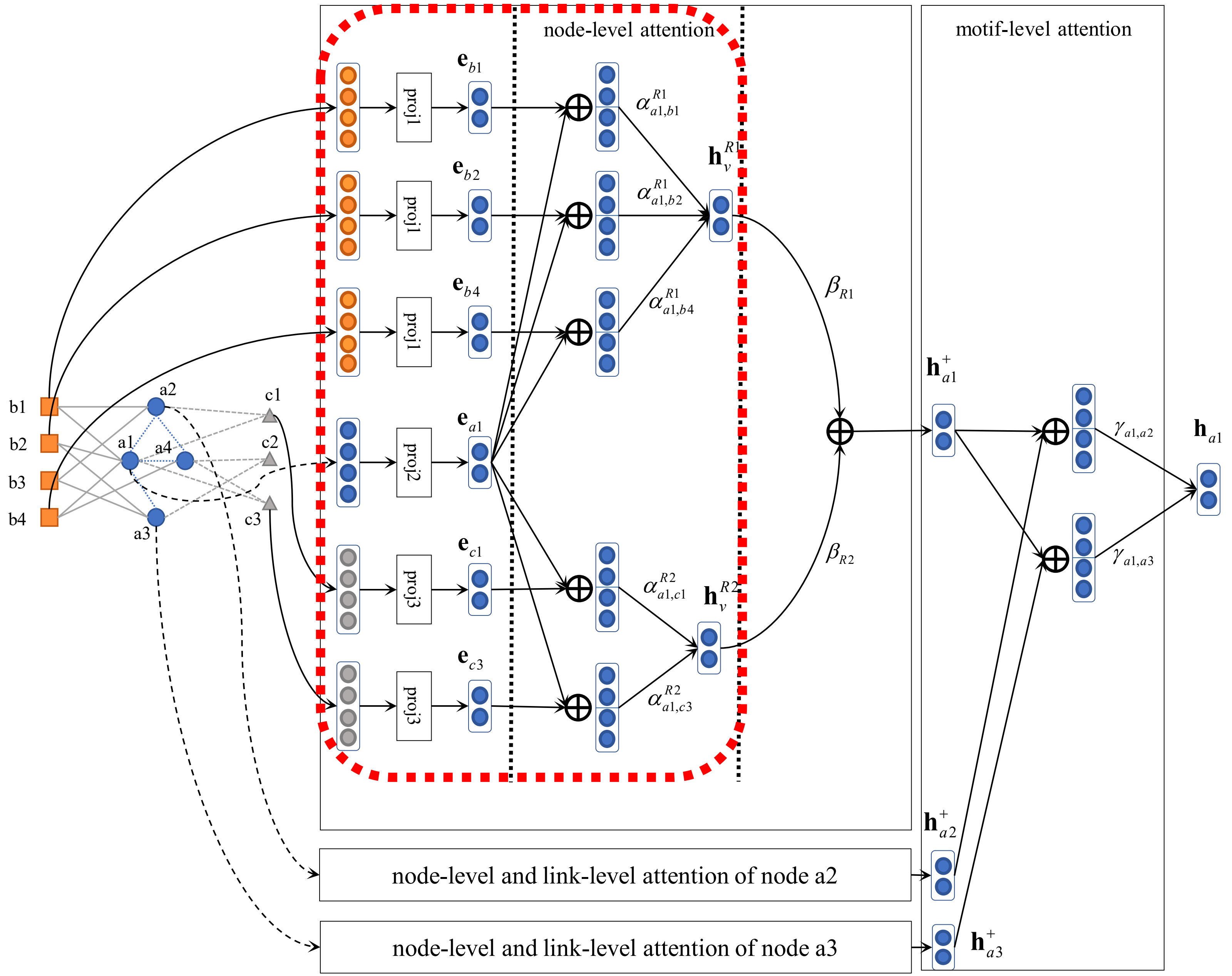
2 StarGAT

Overall Framework



2 StarGAT

Node-Level Aggregation



Transformation matrix

- Type-Specific Transformation

$$\mathbf{e}_v = \mathbf{M}_A \cdot \mathbf{x}_v$$

- Node-level Attention

$$e_{vu}^R = LeakyRelu(\mathbf{a}_R^{\mathrm{T}}[\mathbf{e}_v \| \mathbf{e}_u])$$

$$\alpha_{vu}^R = \frac{\exp(e_{vu}^R)}{\sum_{s \in \mathcal{N}_v^R} \exp(e_{vs}^R)}$$

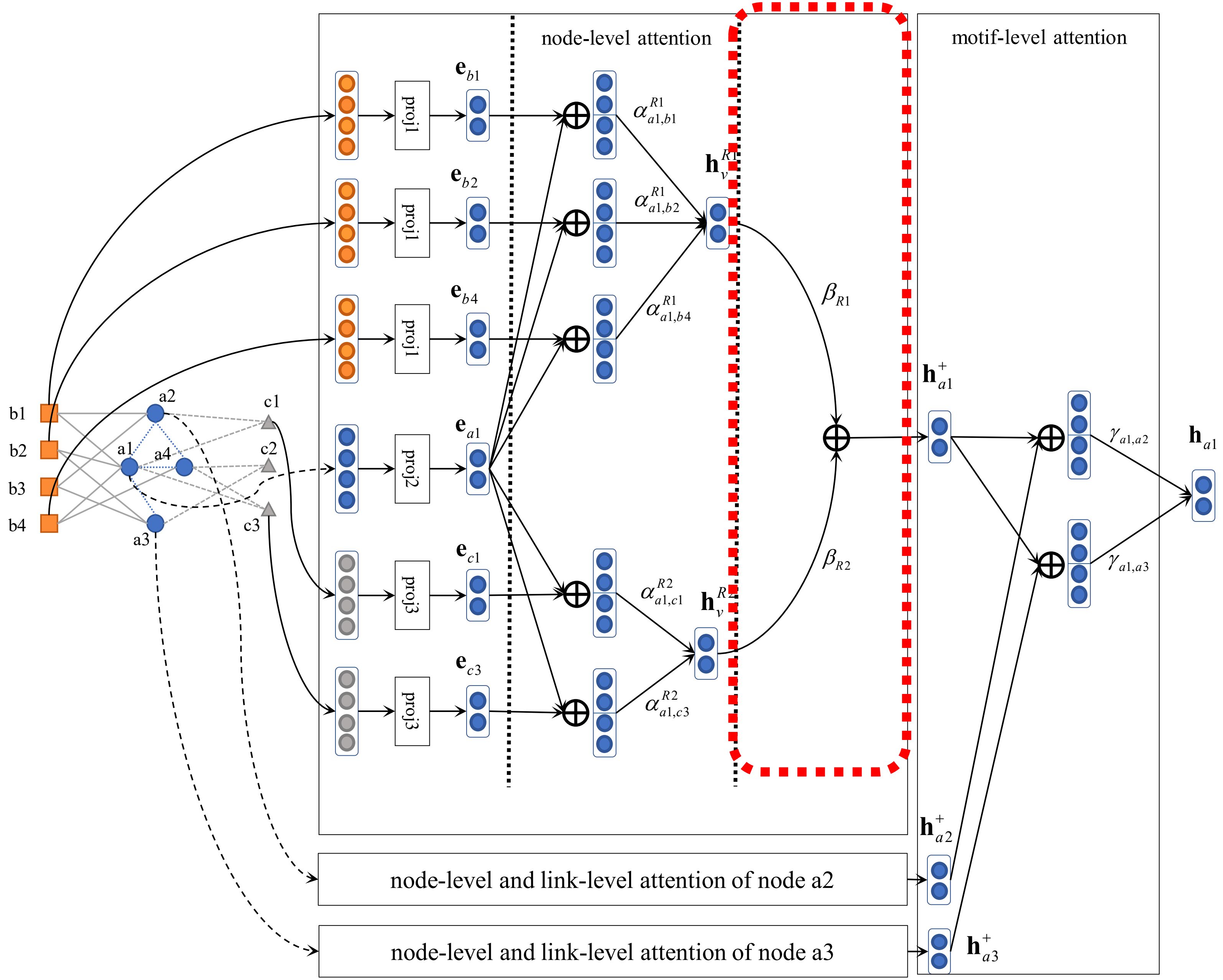
Node-level attention coefficient

- Node-Level Aggregation

$$\mathbf{h}_v^R = \sigma\left(\sum_{u \in \mathcal{N}_v^R} \alpha_{vu}^R \cdot \mathbf{e}_u\right)$$

2 StarGAT

Link-Level Aggregation



- Link-level Attention

$$e^R = \mathbf{q}_R^{\mathrm{T}}\left(\frac{1}{|\mathcal{V}_c|}\sum_{v\in\mathcal{V}_c} tanh[\mathbf{W}_R\mathbf{h}_v^R + \mathbf{b}_R]\right)$$

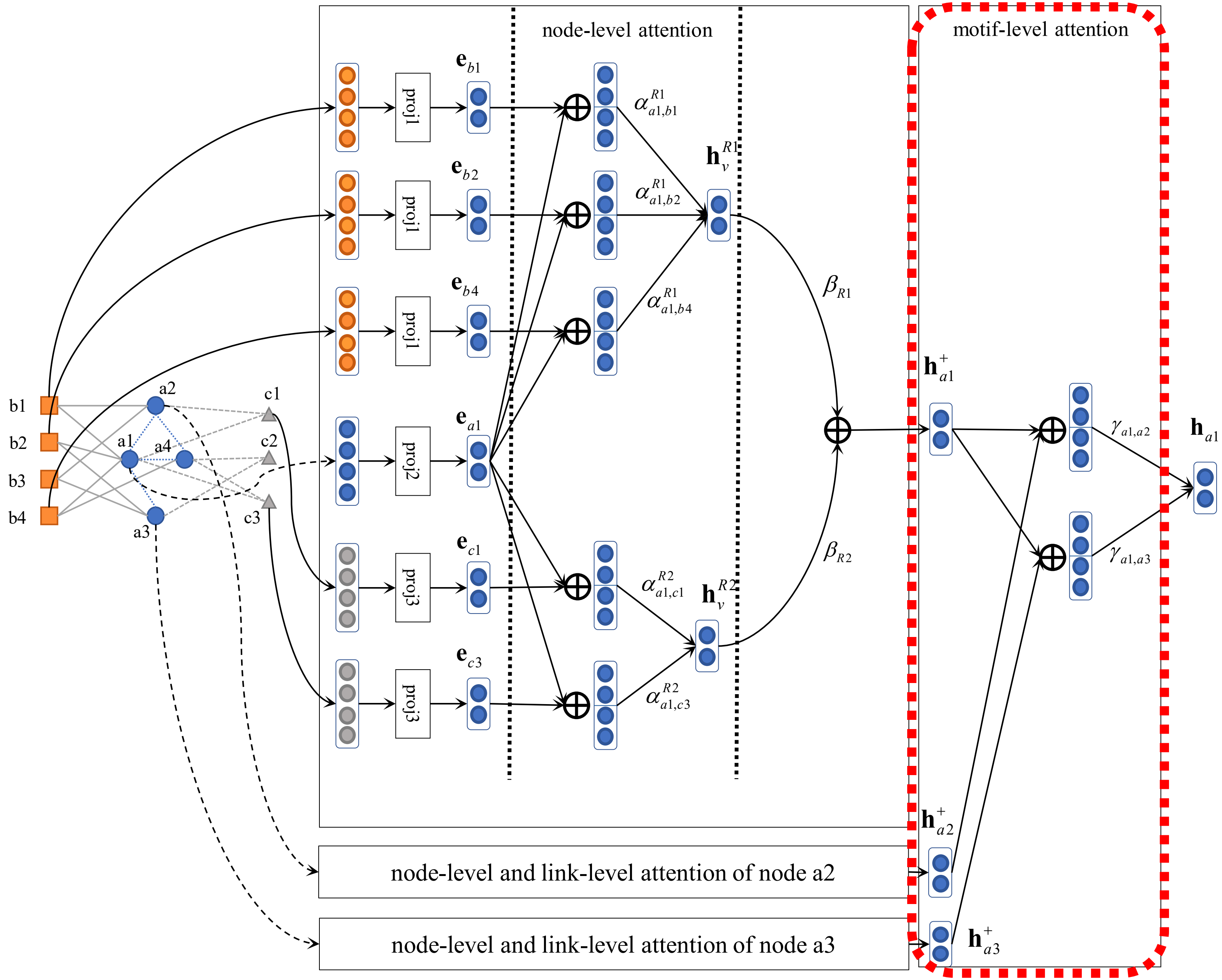
$$\beta_R = \frac{exp(e_R)}{\sum_{i\in\mathcal{R}} exp(e_i)}$$

link-level attention coefficient

- Link-level Aggregation

$$\mathbf{h}_v^+ = \sum_{R\in\mathcal{R}} \beta_R \cdot \mathbf{h}_v^R$$

Link-Level Aggregation



■ Motif-level Attention

$$e_{ij} = LeakyRelu(\mathbf{p}^{\mathrm{T}}[\mathbf{Wh}_i^{+} \| \mathbf{Wh}_j^{+}])$$

$$\gamma_{ij} = \frac{exp(e_{ij})}{\sum_{k \in \mathcal{N}_i} exp(e_{ik})}$$

$$\mathbf{h}_i = \sigma(\sum_{j \in \mathcal{N}_i} \gamma_{ij}^{R} \cdot \mathbf{Wh}_j^{+})$$

$$e_j = \mathbf{p}^{\mathrm{T}}(tanh[\mathbf{Wh}_j^{+} + \mathbf{b}])$$

$$\gamma_j = \frac{exp(e_j)}{\sum_{k \in \mathcal{N}_i} exp(e_k)}$$

$$\mathbf{h}_i = \sum_{j \in \mathcal{N}_i} \gamma_j \cdot \mathbf{h}_j^{+}$$

CONTENTS

1 Backgrounds

2 Proposed Model: StarGAT

3 **Experiments**

4 Conclusions

Baseline Methods

- Deepwalk
- Metapath2vec
- Node2vec
- GCN
- GAT
- HAN
- MAGNN

Tasks

- Node Classification
- Node Clustering
- Ablation Study
- Hyper-Parameter Analysis
- Visualization

Datasets

Datasets	Number of Nodes	Number of Edges
ACM	# paper (P): 4,025 # author (A): 7,167 # term (T): 1,902	# P-A: 37,055 # P-T: 972,973
DBLP	# paper (P): 14,328 # author (A): 4,057 # term (T): 7,723	# P-A: 19,645 # P-T: 85,810
Yelp	# business (B): 2,614 # user (U): 1,286 # service (S): 2 # star level (SL): 9 # reservation (R): 2	# B-U: 30,838 # B-S: 2,614 # B-SL: 2,614 # B-R: 2614

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Node Classification & Node Clustering

NODE CLASSIFICATION RESULTS (%) ON THE THREE REAL-WORLD DATASETS. **BOLD**: BEST; <u>UNDERLINE</u>: RUNNER-UP.

Datasets	Metrics	Deepwalk	Metapath2vec	Node2vec	GCN	GAT	HAN	MAGNN	StarGAT
ACM	Macro-F1	59.44	51.49	<u>73.31</u>	24.85	51.25	65.52	70.40	**82.60**
	Micro-F1	61.91	67.36	<u>74.53</u>	50.17	62.78	69.18	72.03	**83.12**
DBLP	Macro-F1	21.60	58.76	68.20	64.60	66.50	74.49	<u>75.57</u>	**75.65**
	Micro-F1	36.17	66.55	71.73	68.83	70.13	78.53	<u>78.90</u>	**79.15**
Yelp	Macro-F1	48.23	45.48	57.29	54.98	67.52	56.37	<u>71.82</u>	**71.94**
	Micro-F1	65.04	61.38	68.78	72.82	76.23	74.18	<u>77.66</u>	**78.23**

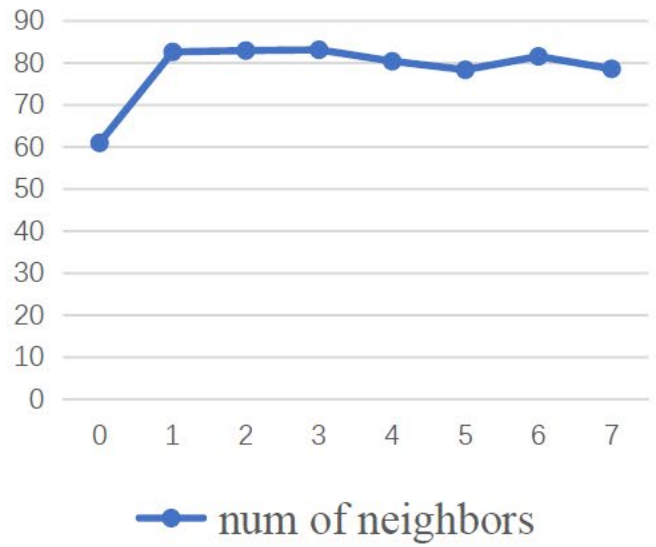
NODE CLUSTERING RESULTS (%) ON THE THREE REAL-WORLD DATASETS. **BOLD**: BEST; <u>UNDERLINE</u>: RUNNER-UP.

Datasets	Metrics	Deepwalk	Metapath2vec	Node2vec	GCN	GAT	HAN	MAGNN	StarGAT
ACM	NMI	2.70	15.02	25.55	4.67	9.98	<u>29.80</u>	29.19	**42.57**
	ARI	2.40	14.20	24.10	1.84	8.74	19.20	<u>31.42</u>	**40.90**
DBLP	NMI	0.11	22.82	2.51	16.34	25.55	<u>40.56</u>	36.21	**40.66**
	ARI	-0.06	15.10	0.84	17.52	29.71	<u>45.71</u>	39.34	**47.83**
Yelp	NMI	25.17	0.94	10.06	36.23	34.83	**40.97**	35.93	<u>40.46</u>
	ARI	22.43	0.74	11.65	34.64	33.52	**44.15**	31.01	<u>38.79</u>

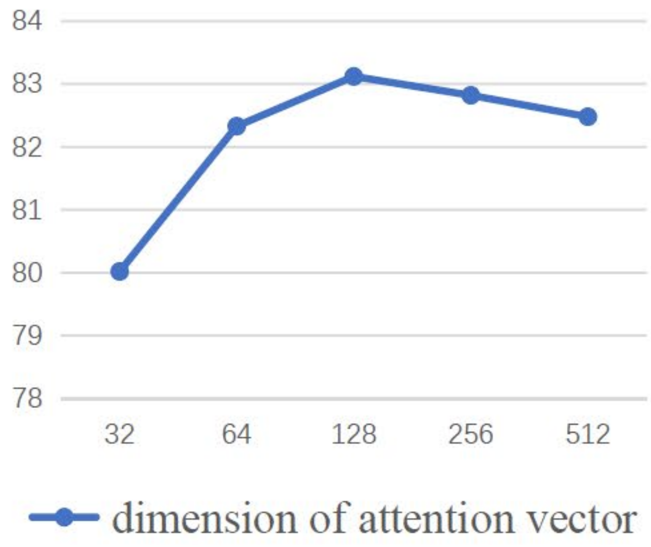
ABLATION STUDY RESULTS (%) ON THE THREE REAL-WORLD DATASETS.

Datasets	Metrics	$init.$	$vr1$	$vr2$	$vr3$
DBLP	Macro-F1	75.65	74.86	73.69	75.41
	Micro-F1	79.15	78.44	77.48	78.87
ACM	Macro-F1	82.60	82.20	82.15	47.50
	Micro-F1	83.12	83.02	82.96	60.99
Yelp	Macro-F1	71.94	54.65	64.09	71.37
	Micro-F1	78.23	54.60	75.68	77.52

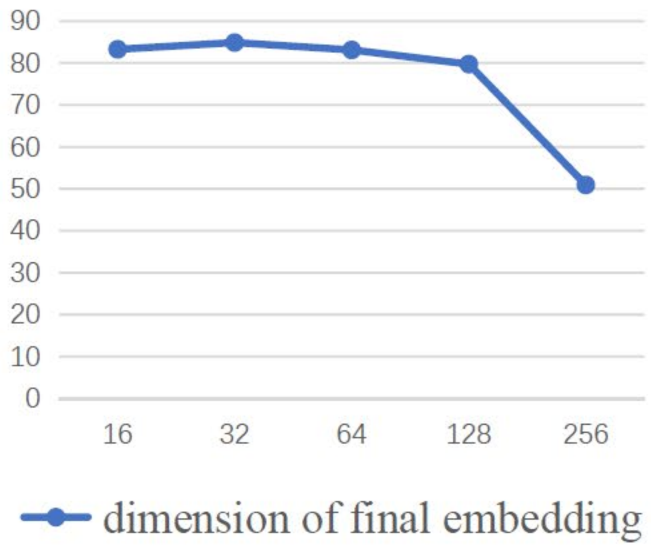
Hyper-parameter Analysis



(a)

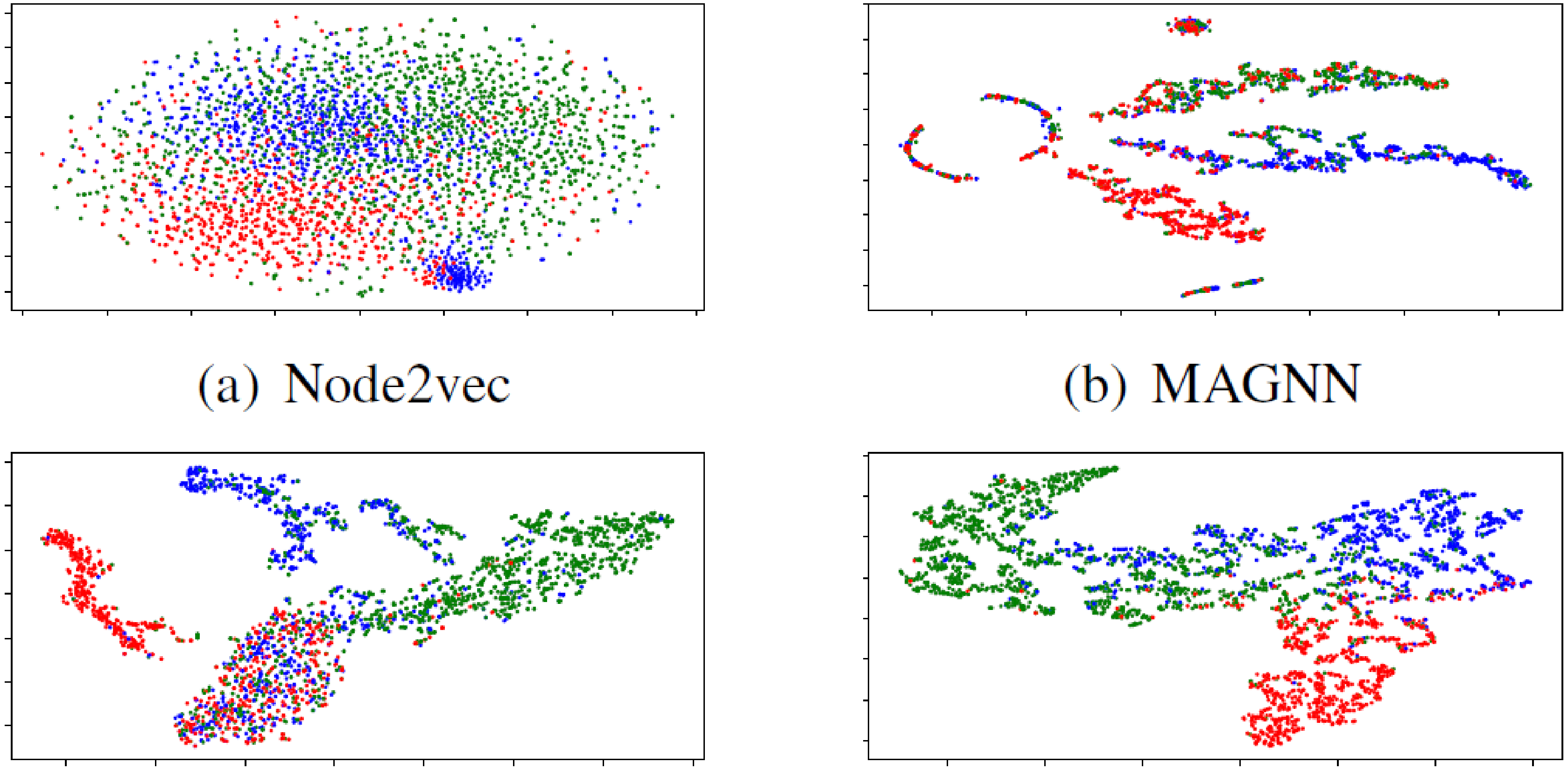


(b)



(c)

Visualization



(a) Node2vec (b) MAGNN

(c) HAN (d) StarGAT

CONTENTS

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- The first attempt to study **motif-level** attention in HIN.
- **Hybrid-order** (from node level to motif level) attention mechanism to boost HIN embedding.
- **State of the art** performance.

THANKS

Thank you!

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