Multiplex Heterogeneous Graph Convolutional Networks

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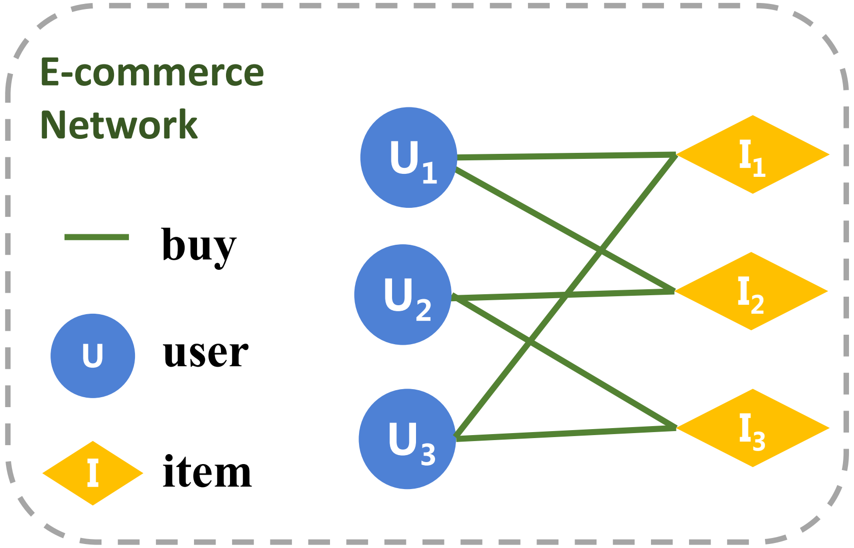
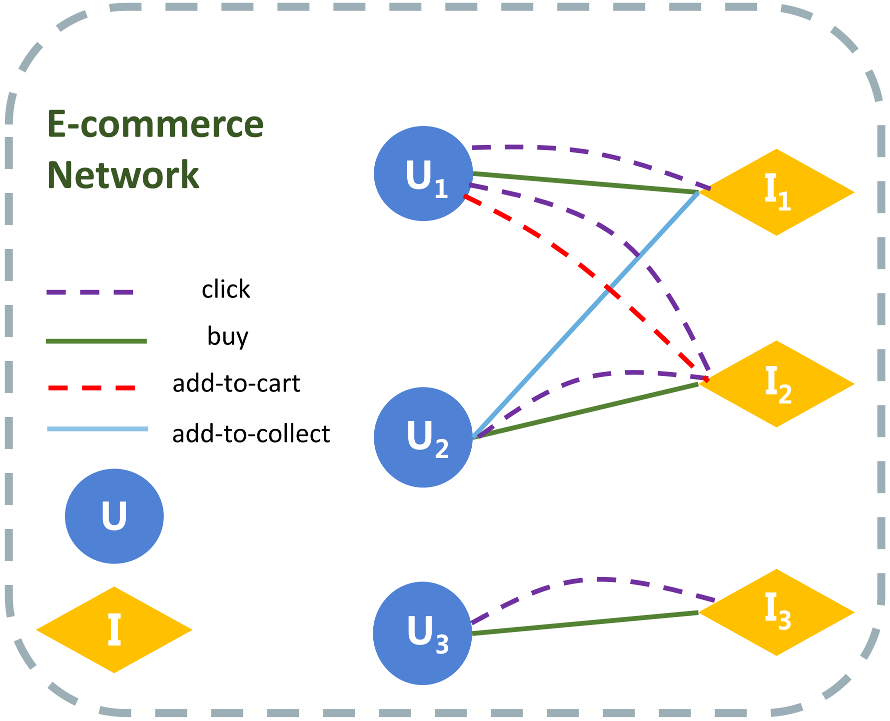
What's Multiplex Heterogeneous Network?

Heterogeneous Network



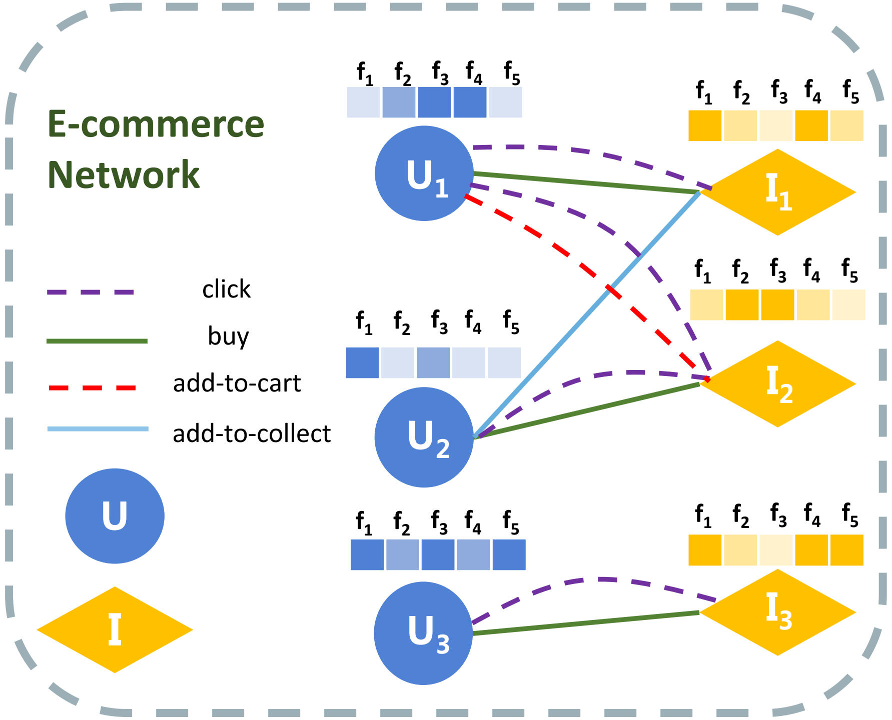
$\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$, with $\phi: \mathcal{V} \to \mathcal{O}$, $\psi: \mathcal{E} \to \mathcal{R}$
and $|\mathcal{O}| + |\mathcal{R}| > 2$

Multiplex Heterogeneous Network



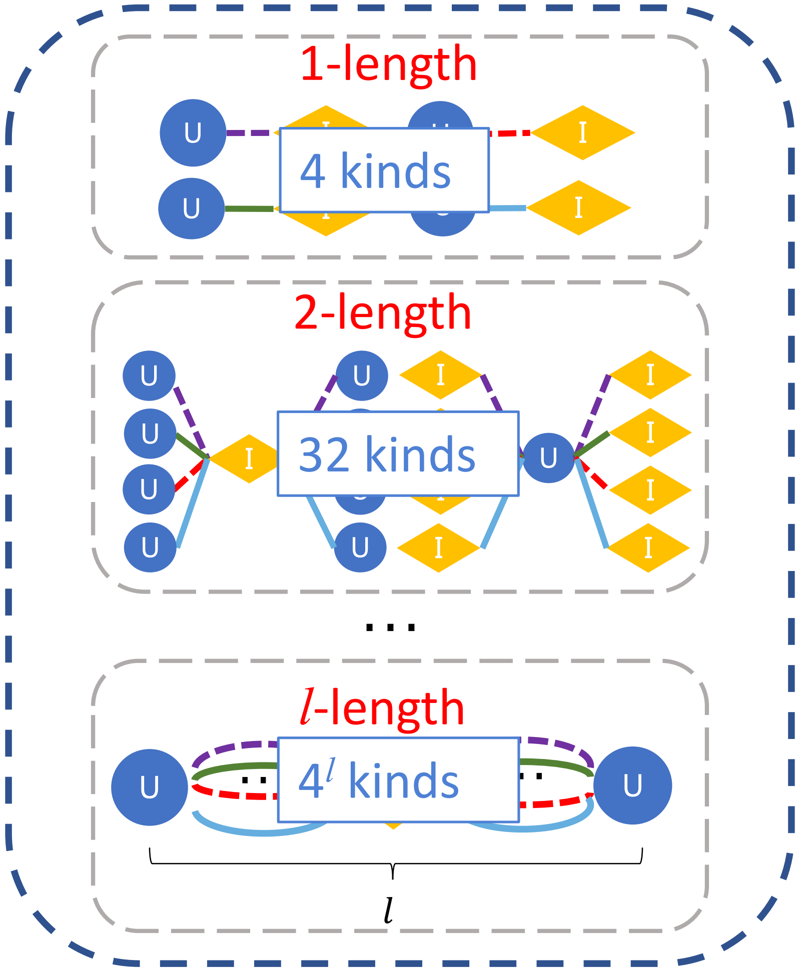
If $|\mathcal{O}| + |\mathcal{R}| > 2$, and existing different types of edges
between same node pairs.

Challenges



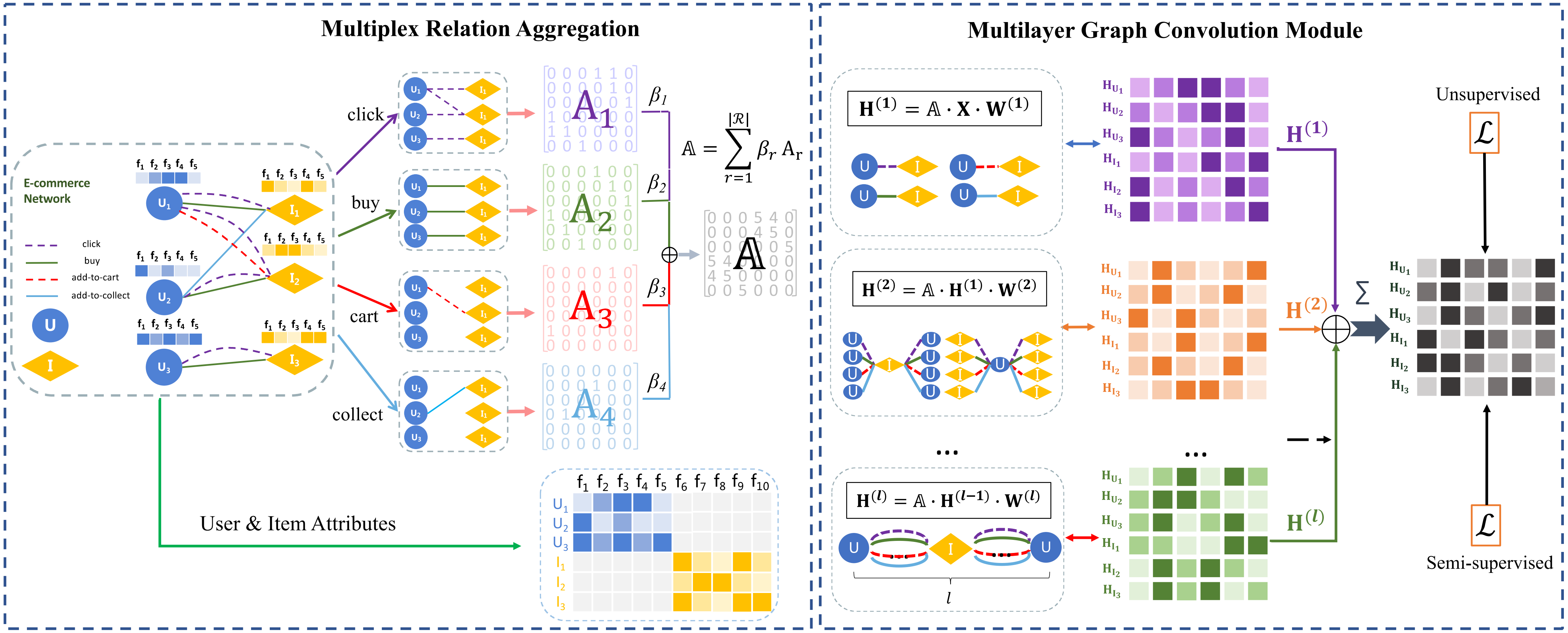
- Heterogeneity vs. Multiplexity
  - Diverse types of nodes and edges.
  - Multiple interactions between the same node pairs.

Challenges



- Heterogeneity vs. Multiplexity
  - Multiple types of nodes and edges.
  - Multiple interactions between the same node pairs.
- Accurate Meta-path design (MAGNN, etc.)
  - Different length.
  - Different interaction order.
- Embedding efficiency
  - Unable to handle large-scale network data

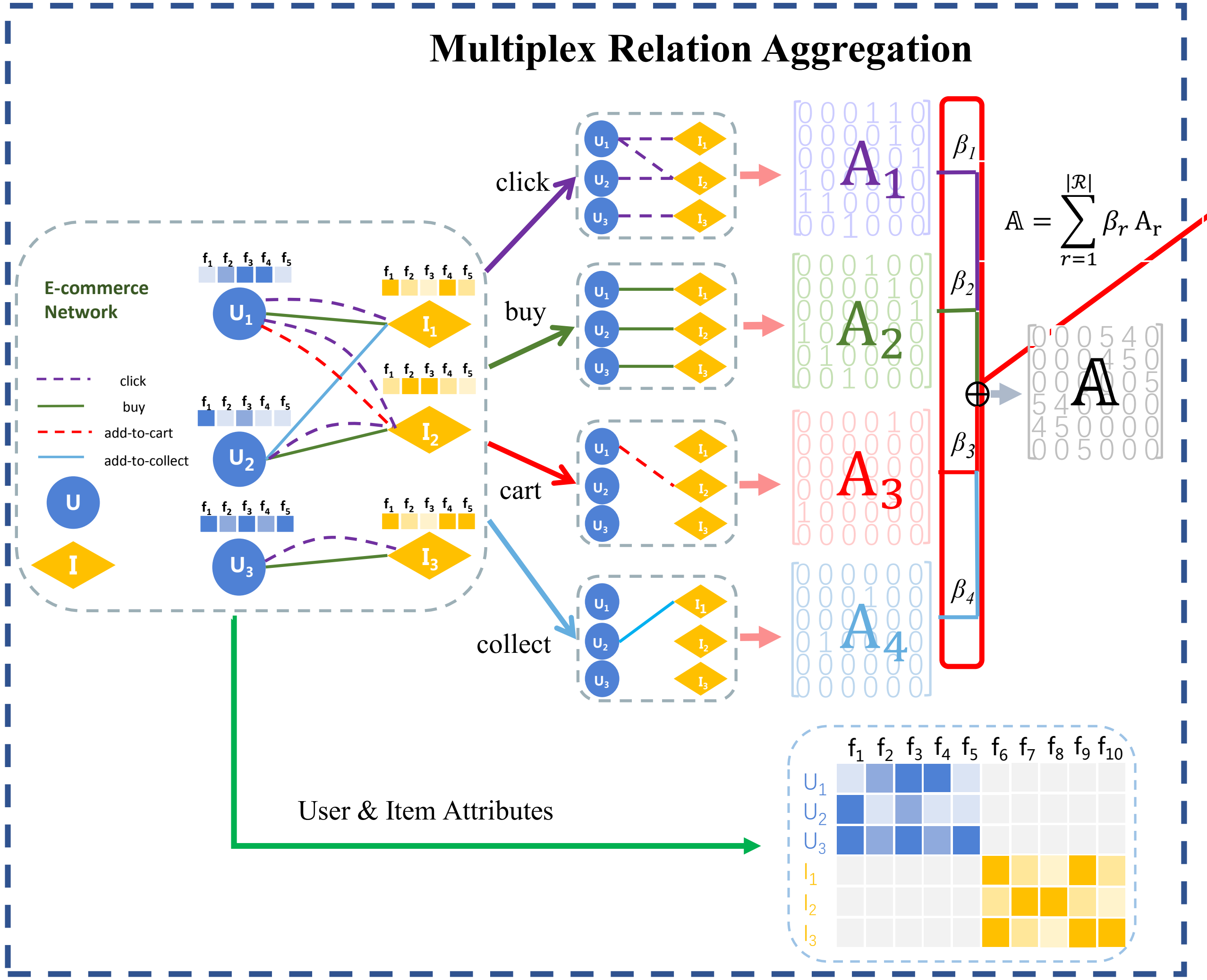
Architecture of Proposed MHGCN



Distinguish the importance of the relations

Automatically capture meta-path information

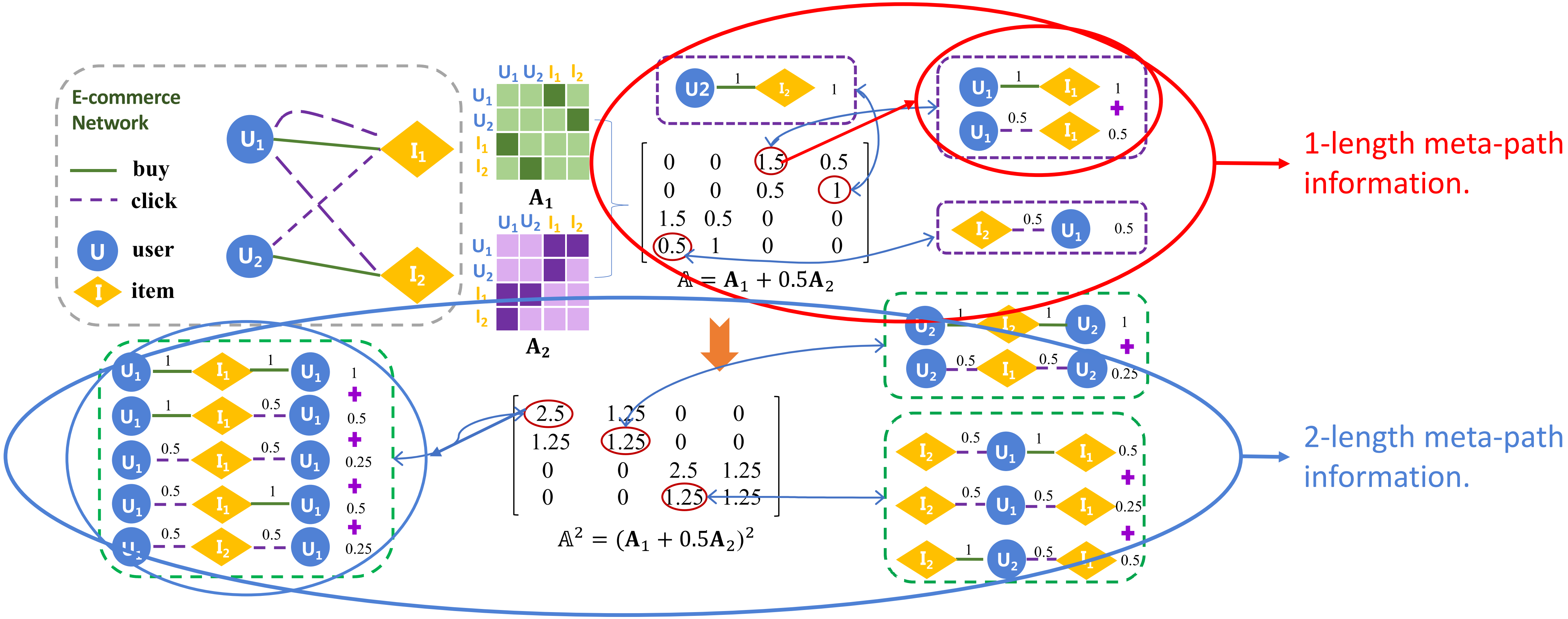
Multiplex Relation Aggregation



Adaptively adjust the relation-aware weights during training.

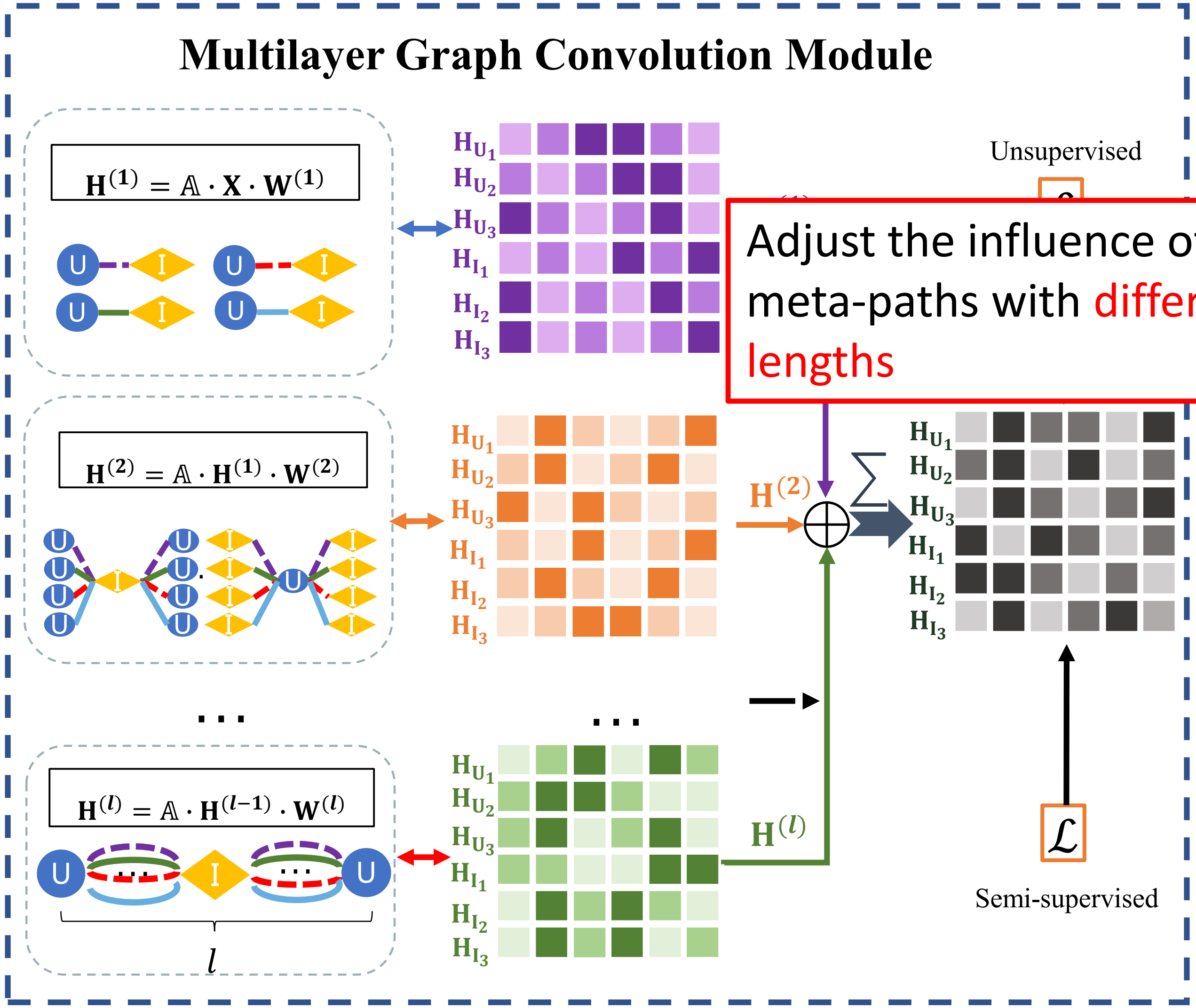
- Decoupling multiplex networks
- Weighted aggregate sub-networks.
- Extracting node attribute features

How to Automatically Capture Heterogeneous Meta-paths?



- Distinguish the importance of different relations.
- Automatically capture the meta-path information.

Multilayer Graph Convolution Module



Adjust the influence of meta-paths with different lengths

One layer convolution:

$$\mathbf{H}^{(1)} = \mathbb{A} \cdot \mathbf{X} \cdot \mathbf{W}^{(1)}$$

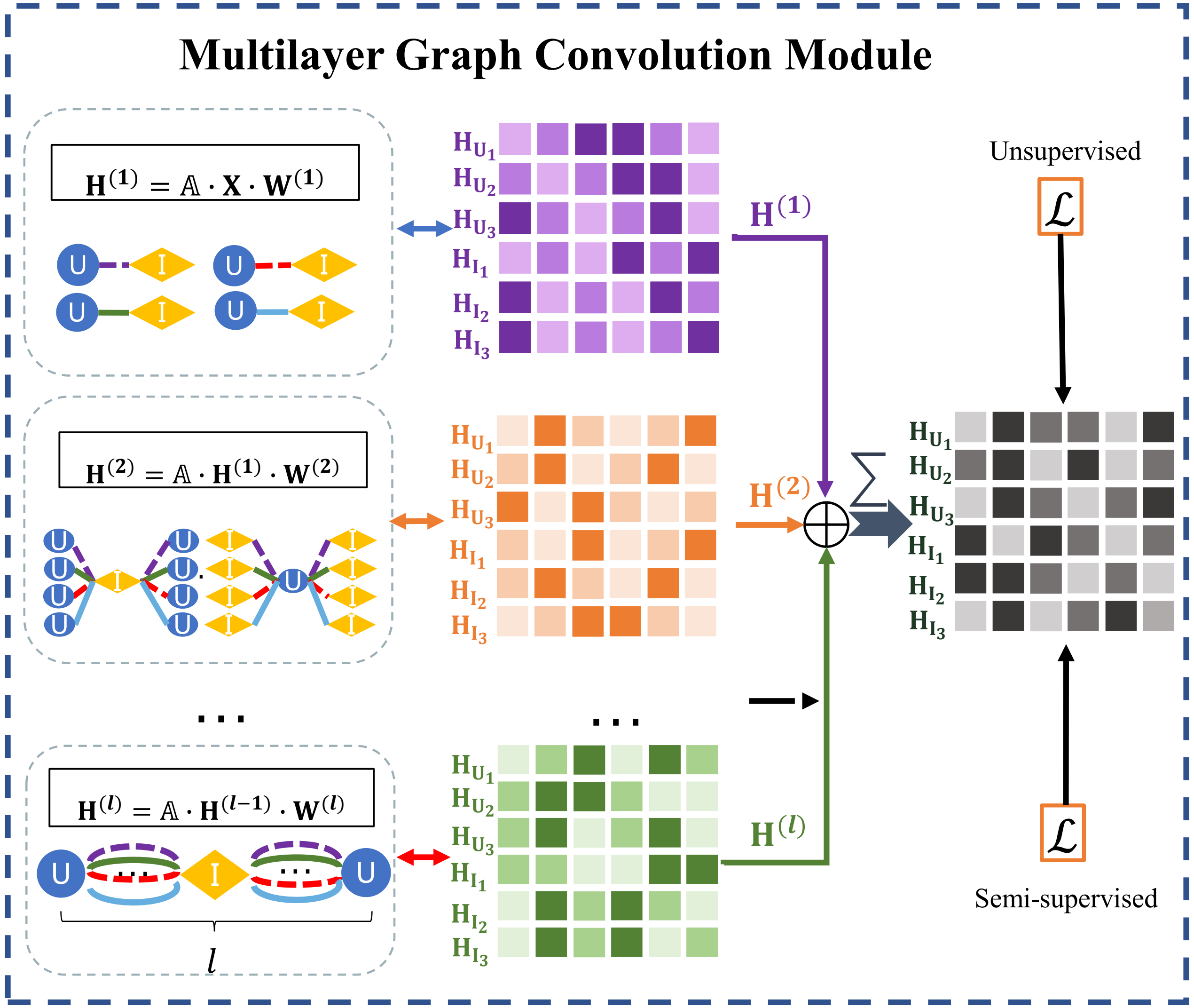
Two layer convolution:

$$\begin{aligned}\mathbf{H}^{(2)} &= \mathbb{A} \cdot \mathbf{H}^{(1)} \cdot \mathbf{W}^{(2)} \\ &= \mathbb{A} \cdot \left(\mathbb{A} \cdot \mathbf{X} \cdot \mathbf{W}^{(1)}\right) \cdot \mathbf{W}^{(2)} \\ &= \mathbb{A}^2 \cdot \mathbf{X} \cdot \mathbf{W}^{(1)} \cdot \mathbf{W}^{(2)}\end{aligned}$$

L-layer convolution:

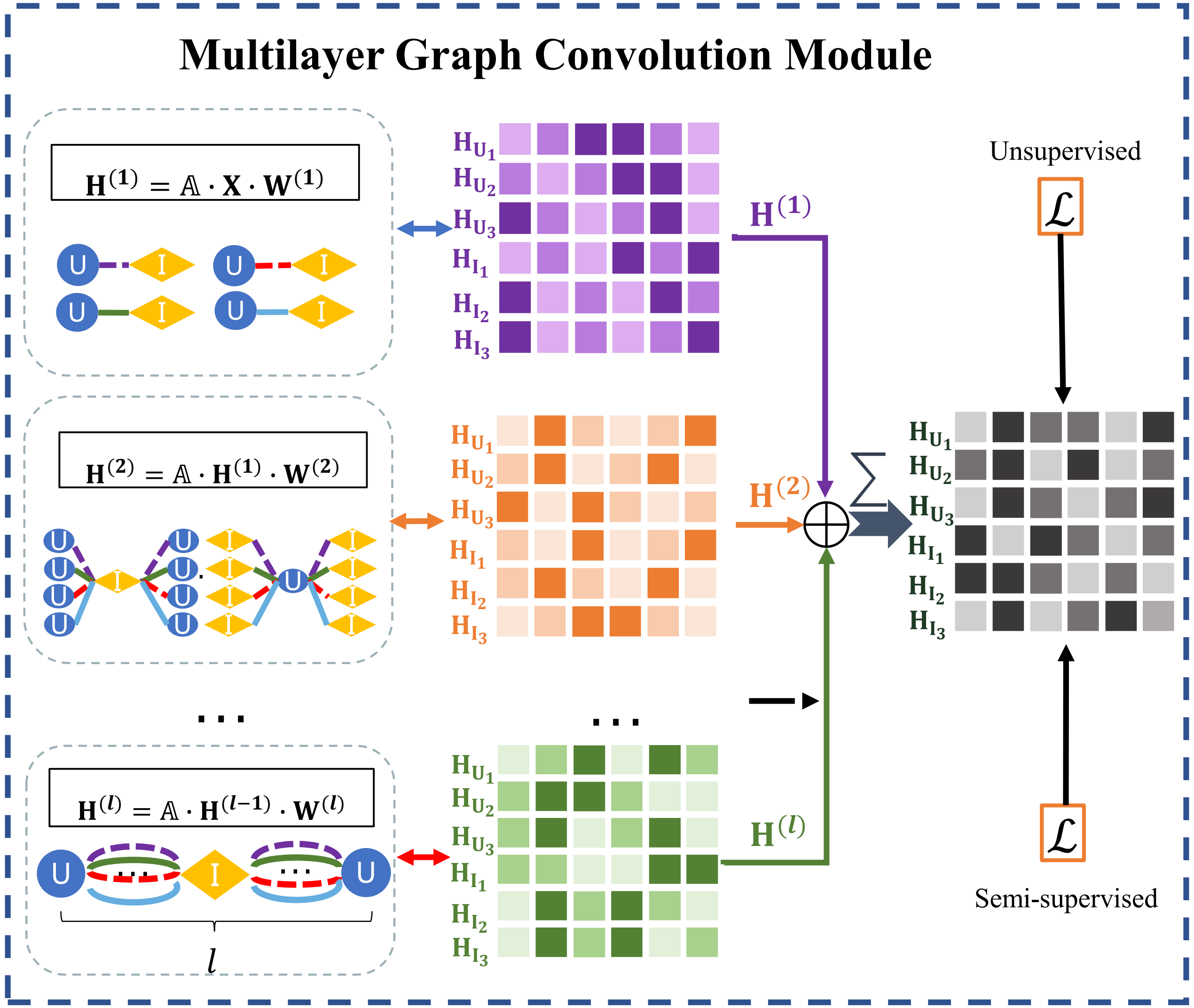
$$\begin{aligned}\mathbf{H}^{(l)} &= \mathbb{A} \cdot \mathbf{H}^{(l-1)} \cdot \mathbf{W}^{(l)} \\ &= \mathbb{A} \cdot \left(\mathbb{A} \cdot \mathbf{H}^{(l-2)} \cdot \mathbf{W}^{(l-1)}\right) \cdot \mathbf{W}^{(l)} \\ &= \underbrace{\mathbb{A} \cdots (\mathbb{A}}_{l} \cdot \mathbf{X} \cdot \underbrace{\mathbf{W}^{(1)}) \cdots \mathbf{W}^{(l)}}_{l} \\ &= \mathbb{A}^{l} \cdot \mathbf{X} \cdot \underbrace{\mathbf{W}^{(1)} \cdots \mathbf{W}^{(l)}}_{l}\end{aligned}$$

Multilayer Graph Convolution Module



$$\mathbf{H} = \frac{1}{l}\sum_{i=1}^{l} \mathbf{H}^{(i)} = \frac{1}{l}\sum_{i=1}^{l} \mathbb{A} \cdot \mathbf{H}^{(i-1)} \cdot \mathbf{W}^{(i)}$$

Multilayer Graph Convolution Module



$$\mathcal{L} = -\sum_{(u,v)\in\Omega} \log \sigma\left(<\mathbf{H}_u^{\mathrm{T}}, \mathbf{H}_v>\right)$$

$$-\sum_{(u',v')\in\Omega^-} \log \sigma\left(<\mathbf{H}_{u'}^{\mathrm{T}}, \mathbf{H}_{v'}>\right)$$

$$\mathcal{L} = -\sum_{i\in\mathcal{V}_{ids}} \mathbf{Y}_i \ln(\mathbb{C}\cdot\mathbf{H}_i)$$

Experiments: Datasets and Baselines

Dataset	#nodes	#edges	#n-type	#e-type	#feat.	Mult.
Alibaba	21,318	41,676	2	4	19	✓
Amazon	10,166	148,865	1	2	1,156	✓
AMiner	58,068	118,939	3	3	4	×
IMDB	12,772	18,644	3	2	1,256	×
DBLP	26,128	119,783	4	3	4,635	×

- Two multiplex heterogeneous networks.
- Three heterogeneous networks.

- Five homogeneous network embedding methods.
- Five heterogeneous network embedding methods.
- Eight multiplex heterogeneous network embedding methods.

Method	Heter. Node	Heter. Edge	Multi.	Attr.	Unsup.	Auto.
node2vec	×	×	×	×	✓	×
RandNE	×	×	×	×	✓	×
FastRP	×	×	×	×	✓	×
SGC	×	×	×	✓	✓/×	×
AM-GCN	×	×	×	✓	×	×
R-GCN	✓	✓	×	✓	✓/×	×
HAN	✓	✓	×	✓	×	×
NARS	✓	✓	×	✓	×	×
MAGNN	✓	✓	×	✓	✓/×	×
HPN	✓	✓	×	✓	✓/×	×
PMNE	×	✓	✓	×	✓	×
MNE	×	✓	✓	×	✓	×
GATNE	✓	✓	✓	✓	✓	×
GTN	✓	✓	✓	✓	×	✓
DMGI	✓	✓	✓	✓	✓	×
FAME	✓	✓	✓	✓	✓	✓
HGSL	✓	✓	✓	✓	×	×
DualHGNN	✓	×	✓	✓	✓	×
MHGCN	✓	✓	✓	✓	✓/×	✓

Experiments: Overview

- Two downstream tasks
  - Link Prediction: vs. 15 baselines
  - Node Classification: vs. 17 baselines
- Ablation Study
  - Verify the effectiveness of each component of our MHGCN.
- Parameter Sensitivity
  - Verify the sensitivity of three important parameters?
- Model Efficiency Analysis
  - Evaluate the efficiency of our proposed MHGCN?

Link Prediction

Method	AMiner R-AUC	AMiner PR-AUC	AMiner F1	Alibaba R-AUC	Alibaba PR-AUC	Alibaba F1	IMDB R-AUC	IMDB PR-AUC	IMDB F1	Amazon R-AUC	Amazon PR-AUC	Amazon F1	DBLP R-AUC	DBLP PR-AUC	DBLP F1
node2vec	0.594	0.663	0.602	0.614	0.580	0.593	0.479	0.568	0.474	0.946	0.944	0.880	0.449	0.452	0.478
RandNE	0.607	0.630	0.608	0.877	0.888	0.826	0.901	0.933	0.839	0.950	0.941	0.903	0.492	0.491	0.493
FastRP	0.620	0.634	0.600	0.927	0.900	0.926	0.869	0.893	0.811	0.954	0.945	0.893	0.515	0.528	0.506
SGC	0.589	0.585	0.567	0.686	0.708	0.623	0.826	0.889	0.769	0.791	0.802	0.760	0.601	0.606	0.587
R-GCN	0.599	0.601	0.610	0.674	0.710	0.629	0.826	0.878	0.790	0.811	0.820	0.783	0.589	0.592	0.566
MAGNN	0.663	0.681	0.666	0.961	0.963	0.948	0.912	0.923	0.887	0.958	0.949	0.915	0.690	0.699	0.684
HPN	0.658	0.664	0.660	0.958	0.961	0.950	0.900	0.903	0.892	0.949	0.949	0.904	0.692	0.710	0.687
PMNE-n	0.651	0.669	0.677	0.966	0.973	0.891	0.674	0.683	0.646	0.956	0.945	0.893	0.672	0.679	0.663
PMNE-r	0.615	0.653	0.662	0.859	0.915	0.824	0.646	0.646	0.613	0.884	0.890	0.796	0.637	0.640	0.629
PMNE-c	0.613	0.635	0.657	0.597	0.591	0.664	0.651	0.634	0.630	0.934	0.934	0.868	0.622	0.625	0.609
MNE	0.660	0.672	0.681	0.944	0.946	0.901	0.688	0.701	0.681	0.941	0.943	0.912	0.657	0.660	0.635
GATNE	OOT	OOT	OOT	0.981	0.986	0.952	0.872	0.878	0.791	0.963	0.948	0.914	[illegible]	[illegible]	OOT
DMGI	OOM	OOM	OOM	0.857	0.781	0.784	0.926	0.935	0.873	0.905	0.878	0.847	[illegible]	[illegible]	0.601
FAME	0.687	0.747	0.726	0.993	0.996	0.979	0.944	0.959	0.897	0.959	0.950	0.900	[illegible]	[illegible]	0.633
DualHGNN	/	/	/	0.974	0.977	0.966	/	/	/	/	/	/	[illegible]	[illegible]	/
MHGCN	**0.711**	**0.753**	**0.730**	**0.997**	**0.997**	**0.992**	**0.967**	**0.966**	**0.959**	**0.972**	**0.974**	**0.961**	**0.718**	**0.722**	**0.703**

average 5.68% gains

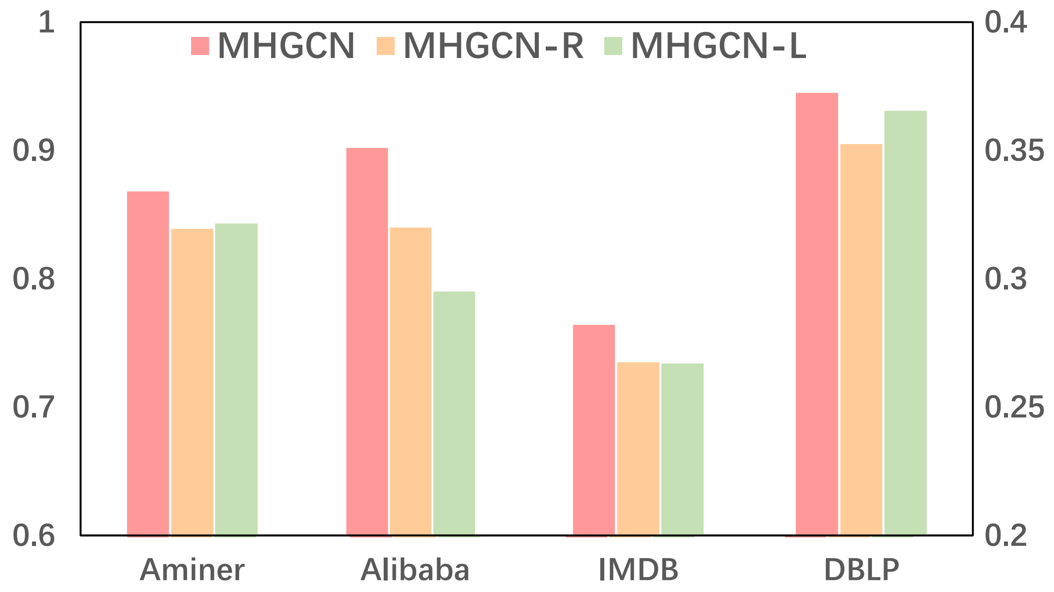
MHGCN achieves average gains of 5.68% F1 score in comparison to the best performed GNN baselines across all datasets.

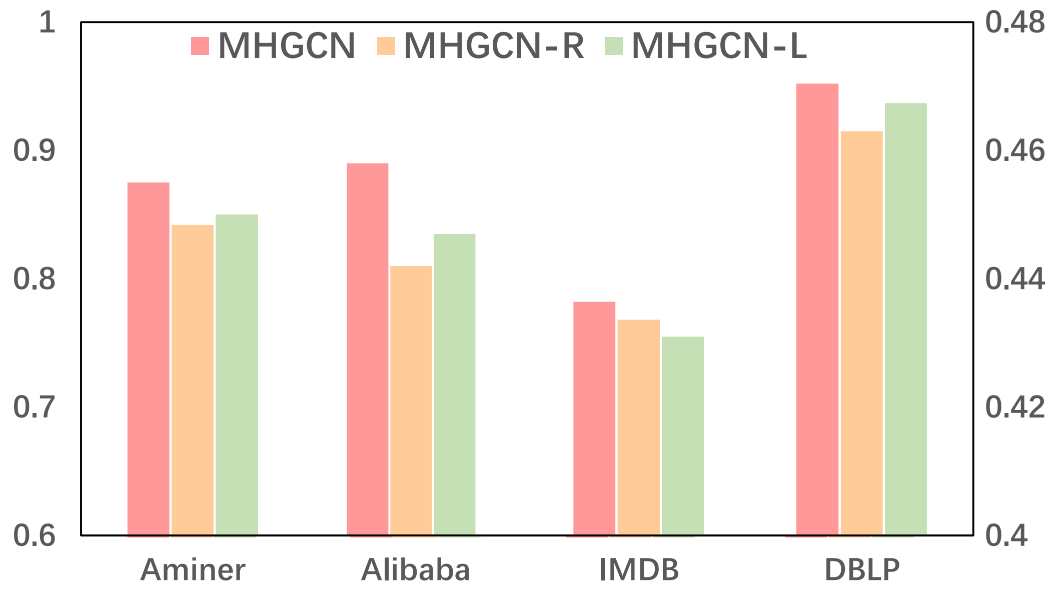
Node Classification

Method	AMiner		Alibaba		IMDB		DBLP	
	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1
node2vec	0.522 (0.0032)	0.532 (0.0051)	0.238 (0.0125)	0.347 (0.0093)	0.363 (0.0237)	0.382 (0.0703)	0.352 (0.0103)	0.351 (0.0112)
RandNE	0.641 (0.0074)	0.672 (0.0064)	0.319 (0.0170)	0.358 (0.0093)	0.373 (0.0143)	0.392 (0.0185)	0.351 (0.0153)	0.372 (0.0150)
FastRP	0.650 (0.0086)	0.690 (0.0074)	0.301 (0.0180)	0.392 (0.0119)	0.363 (0.0236)	0.381 (0.0140)	0.343 (0.0201)	0.375 (0.0199)
MNE	0.643 (0.0069)	0.686 (0.0045)	0.289 (0.0155)	0.390 (0.0021)	0.374 (0.0153)	0.382 (0.0680)	0.366 (0.0117)	0.384 (0.0109)
GATNE	OOT	OOT	0.291 (0.0086)	0.390 (0.0014)	0.369 (0.0132)	0.333 (0.0005)	OOT	OOT
DMGI	0.473 (0.0155)	0.626 (0.0093)	0.220 (0.0214)	0.392 (0.0026)	0.548 (0.0190)	0.544 (0.0189)	0.781 (0.0303)	0.787 (0.0235)
FAME	0.722 (0.0114)	0.727 (0.0091)	0.323 (0.0154)	0.393 (0.0060)	0.593 (0.0135)	0.594 (0.0143)	0.842 (0.0183)	0.868 (0.0127)
DualHGNN	/	/	0.347 (0.0114)	0.402 (0.0127)	/	/	/	/
SGC	0.516 (0.0047)	0.587 (0.0157)	0.286 (0.0231)	0.361 (0.0175)	0.489 (0.0106)	0.563 (0.0133)	0.622 (0.0009)	0.623 (0.0009)
AM-GCN	0.702 (0.0175)	0.713 (0.0223)	0.307 (0.0232)	0.399 (0.0156)	0.610 (0.0021)	0.640 (0.0013)	0.867 (0.0105)	0.878 (0.0112)
R-GCN	0.690 (0.0078)	0.692 (0.0106)	0.265 (0.0326)	0.381 (0.0125)	0.544 (0.0172)	0.572 (0.0145)	0.862 (0.0053)	0.870 (0.0070)
HAN	0.690 (0.0149)	0.726 (0.0086)	0.275 (0.0327)	0.392 (0.0081)	0.552 (0.0112)	0.568 (0.0078)	0.806 (0.0078)	0.813 (0.0100)
NARS	0.722 (0.0103)	0.721 (0.0097)	0.297 (0. [illegible]	[illegible]	[illegible]	[illegible] .0048)	0.794 (0.0255)	0.804 (0.0320)
MAGNN	0.755 (0.0105)	0.757 (0.0133)	0.348 (0. [illegible]	[illegible]	[illegible]	[illegible] .0089)	0.881 (0.0284)	0.895 (0.0396)
HPN	0.710 (0.0612)	0.732 (0.0490)	0.263 (0. [illegible]	[illegible]	[illegible]	[illegible] .0021)	0.822 (0.0201)	0.830 (0.0201)
GTN	OOM	OOM	0.255 (0.0420)	0.392 (0.0071)	0.615 (0.0108)	0.616 (0.0093)	0.852 (0.0137)	0.868 (0.0125)
HGSL	0.754 (0.0100)	0.758 (0.0103)	0.338 (0.0121)	0.398 (0.0238)	0.620 (0.0048)	0.638 (0.0030)	0.893 (0.0284)	0.902 (0.0396)
MHGCN	**0.868 (0.0160)**	**0.875 (0.0200)**	**0.351 (0.0204)**	**0.458 (0.0160)**	**0.764 (0.0145)**	**0.782 (0.0138)**	**0.945 (0.0221)**	**0.952 (0.0203)**

23.23% improvement on Macro-F1
22.19% improvement on Micro-F1

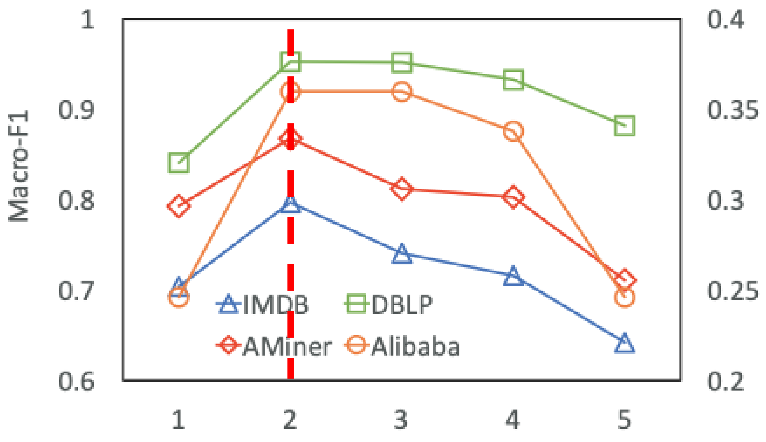
Ablation Study



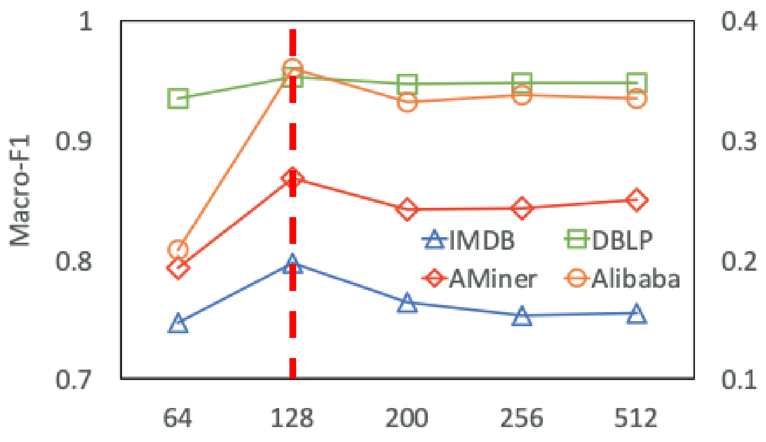


- MHGCN-R does not consider the importance of different relations.
  - ➢ Demonstrate the crucial role of our designed multiplex relation aggregation module.
- MHGCN-L uses only a two-layer GCN to obtain the embedding
  - ➢ Reflect the importance of our multilayer graph convolution module.

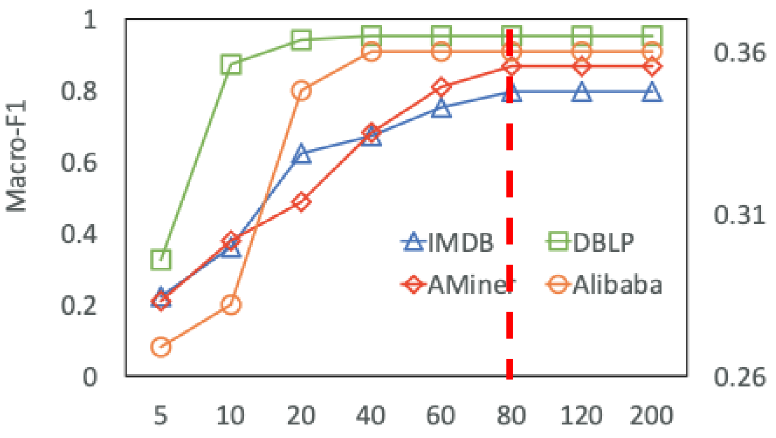
Parameter Sensitivity



(a) Macro-F1 score *w.r.t.* #layers



(b) Macro-F1 score *w.r.t.* dimension d



(c) Macro-F1 score *w.r.t.* #rounds

- 1-length and 2-length meta-path already effectively capture the topological structures of network.
- Achieve the best performance when embedding dimension d = 128.
- Achieve the stable performance within 80 rounds on all tested datasets.

Model Efficiency Analysis

Method	AMiner	Alibaba	IMDB	DBLP
AM-GCN	8703.71	2519.82	24280.12	2786.73
R-GCN	**153.04**	301.25	155.40	192.85
HAN	87105.55	4226.95	70510	22315.36
NARS	172.21	**211.54**	**75.81**	**108.54**
MAGNN	10361.20	2320.62	731.03	2125.33
HPN	172.82	249.47	176.64	109.49
GTN	OOM	21166.83	4287.20	18233.64
HGSL	1684.03	2120.93	1758.21	2037.10
DualHGN	/	11295.92	/	/
MHGCN	645.20	996.52	677.23	970.29
Speedup*	**135.05×**	**4.37×**	**104.15×**	**23.01×**
Speedup**	/	**21.25×**	**6.33×**	**18.80×**

* Speedup of MHGCN over HAN.
** Speedup of MHGCN over GTN.
OOM: Out Of Memory.

- Adopt the idea of simplifying graph convolutional networks
- Ensure efficiency with high performance
  - 135 times faster than HAN on AMiner.
  - 21 times faster than GTN on Alibaba.

Conclusion

- We propose an effective graph convolution network model for attaibuted multiplex heterogeneous networks.
- Our model can well deal with the multilayered nature of multiplex networks and distinguish the importance of different relations in heterogeneous networks.
- Our model can automatically capture the useful relation-aware meta-path information in multiplex heterogeneous networks.
- Experiments on five real-word datasets demonstrate the effectiveness and efficiency of the proposed model.

Thanks for Listening

Q & A

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