Hypergraph Representation Learning and Applications

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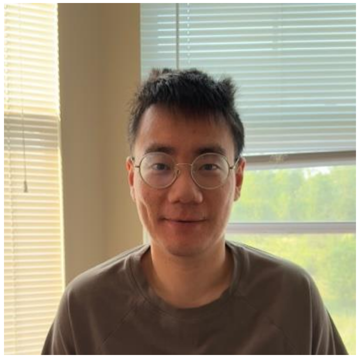
CSE 60745

Self Introduction

- Fourth-year PhD Student from Ye's Lab



- Research Focus:
  - (Hyper) Graph Learning
  - LLMs Integrations with Graph
- Applications:
  - AI to Combat Opioid Crisis
  - Graph as tools to solve real-world problems

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What is Hypergraph

Hypergraph – “General” Version of Graph

$$\mathcal{G} = (\mathcal{V}, \mathcal{E}), \mathcal{E} \subseteq \{\{v_1, v_2\} \,|\, v_1, v_2 \in \mathcal{V}\}$$

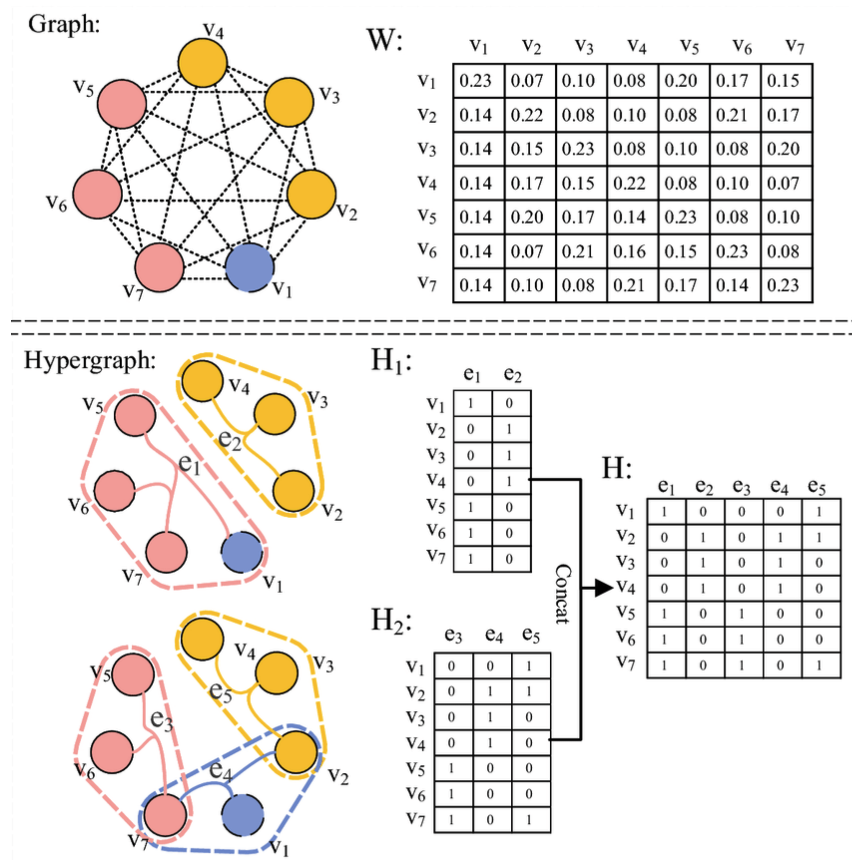
$$\mathcal{H} = (\mathcal{V}, \mathcal{E}), \mathcal{E} \subseteq \mathcal{P}(\mathcal{V}) \backslash \{\emptyset\}$$

$\mathcal{P}(\mathcal{V})$ is Power Set

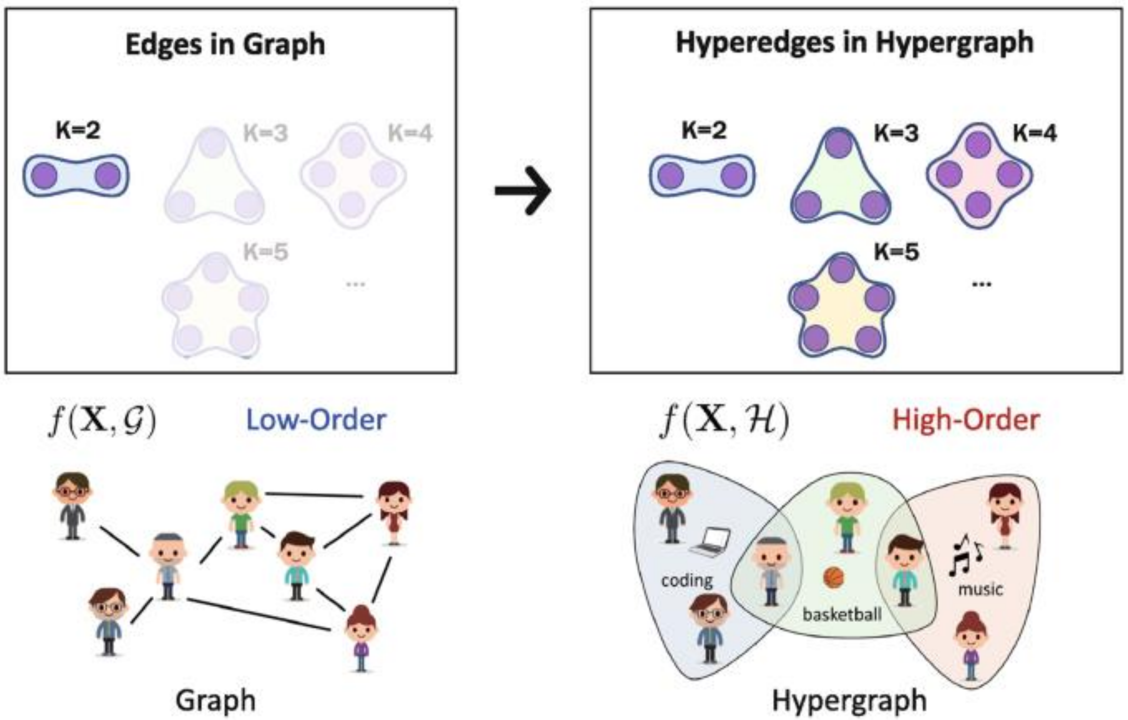
K-Uniform Hypergraph

$$\mathcal{H} = (\mathcal{V}, \mathcal{E}), \mathcal{E} \subseteq \{e \,|\, e \subseteq \mathcal{V}, |e| = k\}$$

Every 2-uniform hypergraph is (equivalent to) a single graph



What is Hypergraph (Cont'd)

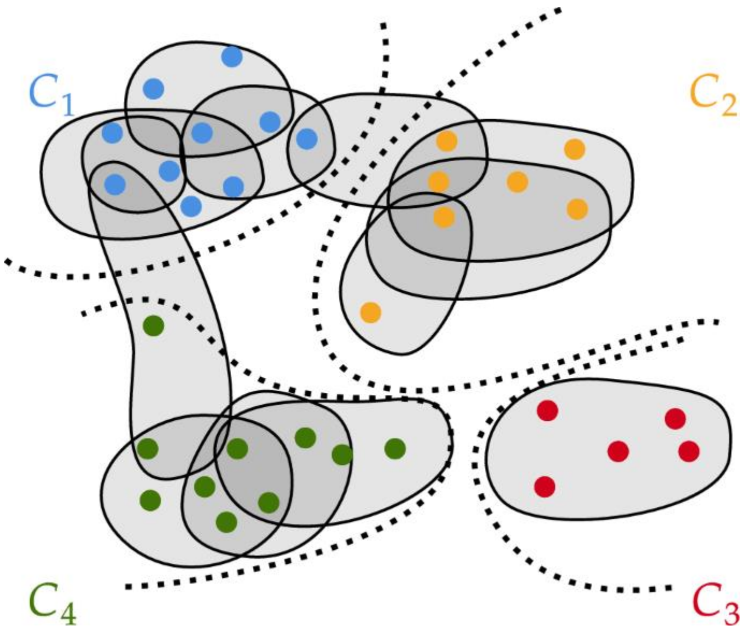


Why Hypergraph

- Graphs that depict pair-wise relations are not enough
- Higher-order Interactions
  - A group of people follows a celebrity on social media.
  - One paper has multiple authors.
  - Group conversations.

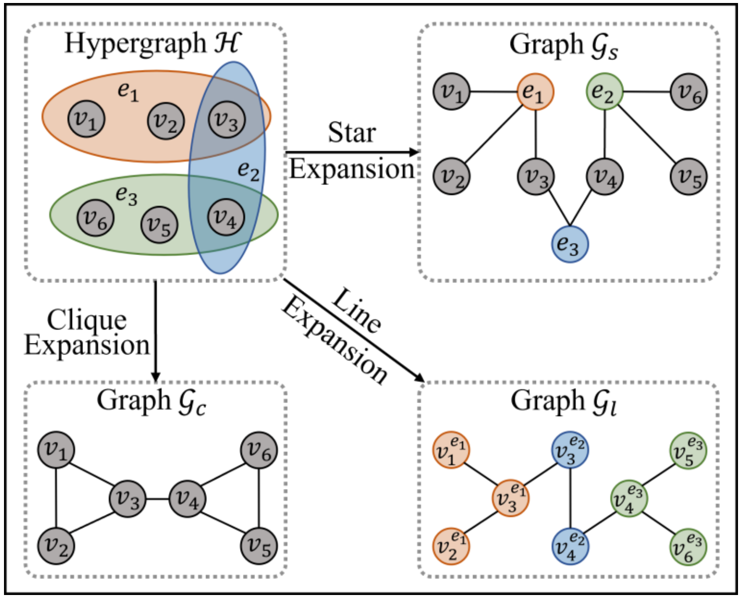
Why Hypergraph (Cont'd)

- Spectral Clustering
  - A hyperedge naturally forms a "cluster"
  - Community Detection
- Generalizability and Flexibility
  - Any method/algorithm for general hypergraphs is applicable to graphs



Unique Challenges

- Preserving Higher-order Information
  - Hard to model hypergraphs with complex structures during representation learning
  - Converting hypergraphs into graphs potentially leads to information loss
  - Capturing many-to-many interaction patterns is a core open problem.



Unique Challenges (Cont'd)

- Variable Hyperedge Sizes
  - Hyperedges may contain various sizes of nodes, ranging from 2 to N
  - Need carefully designed aggregation methods for nodes/hypergraphs.

Unique Challenges (Cont'd)

- Hypergraph Heterophily
  - Node-level heterophily (similar to graphs)
  - Hyperedge-level heterophily
    - Nodes in a hyperedge may come from different classes

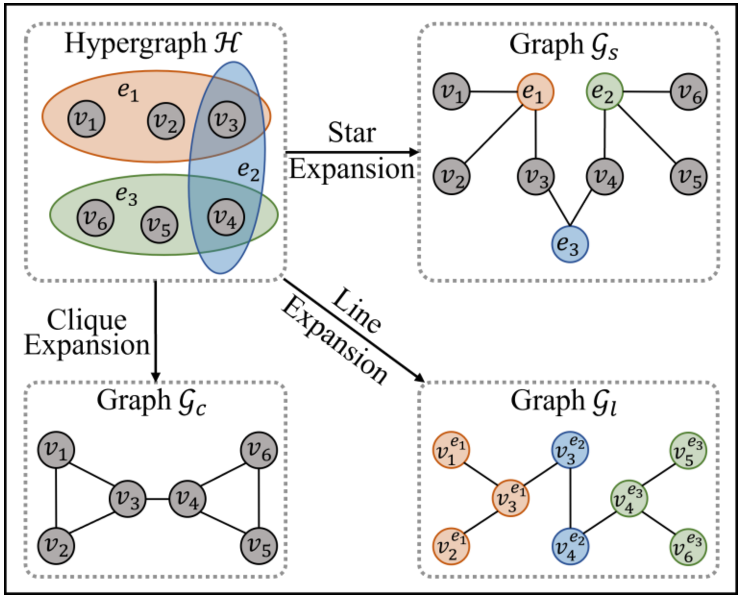
In-Class Activity 1

- Identify hypergraph structures in real-world scenarios
  - Shopping Trips
  - Course Enrollment
  - Social Media

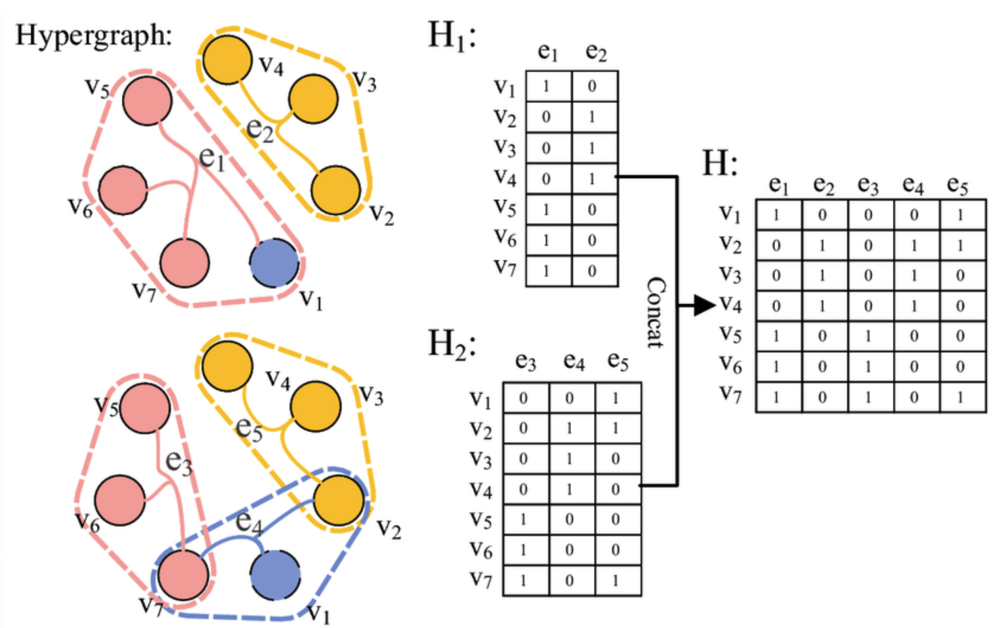
Example:
Co-authorship networks
Nodes: authors, Hyperedges: co-authored papers.
A hyperedge depicts a co-authored relationship about a paper.

Hypergraph Representation Leaning

- Hypergraph Neural Networks (HyGNNs)
  - Clique Expansion based (CE)
    - HGNN (AAAI'19), HyperGCN (NeurIPS'19), UniGCN (IJCAI'21), SheafHGNN (NeurIPS'23)
  - Star Expansion based (SE)
    - AllSet (ICLR'22), ED-HNN (ICLR'23), BHyGNN (ICDM'25)



CE-based HyGNNs

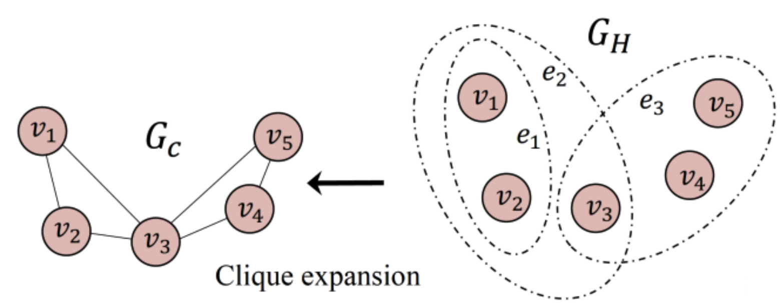


Hypergraph Neural Networks. AAAI'19

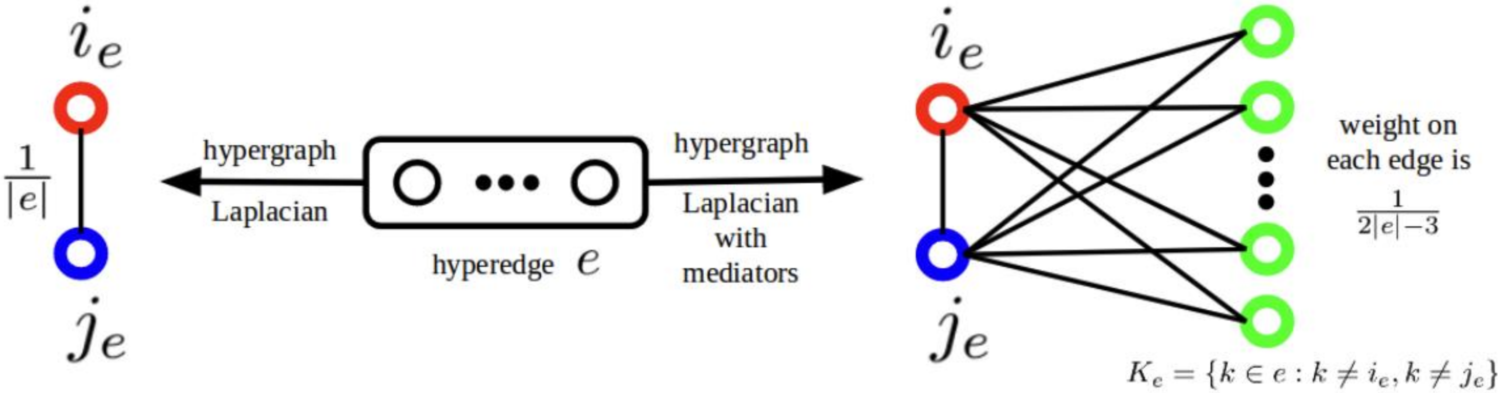
- A Convolution Layer:

$$\mathbf{Y} = \boxed{\mathbf{D}_{\mathbf{v}}^{-1/2}\mathbf{H}\mathbf{W}\mathbf{D}_{\mathbf{e}}^{-1}\mathbf{H}^{\top}\mathbf{D}_{\mathbf{v}}^{-1/2}}\mathbf{X}\boldsymbol{\Theta}$$

Convert an incidence matrix H into an adjacency matrix via Clique Expansion



HGNN vs HyperGCN



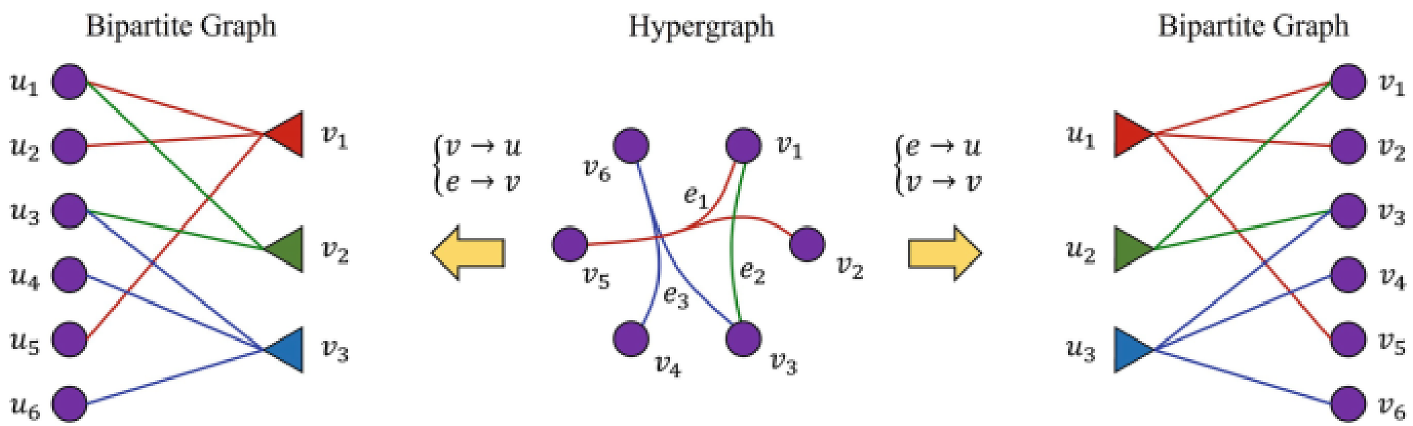
Hypergraph Neural Networks. AAAI'19

HyperGCN: A New Method for Training Graph Convolutional Networks on Hypergraphs. NeurIPs'19

Clique Expansion

Incomplete Clique Expansion

SE-based HyGNNs



$$\mathbf{B} = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\mathbf{H} = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\mathbf{B} = \begin{bmatrix} 1 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 1 \end{bmatrix}$$

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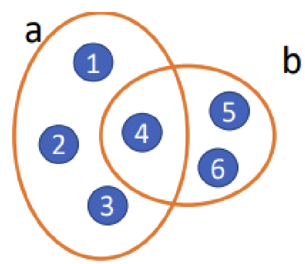
SE-based HyGNNs (Cont'd)

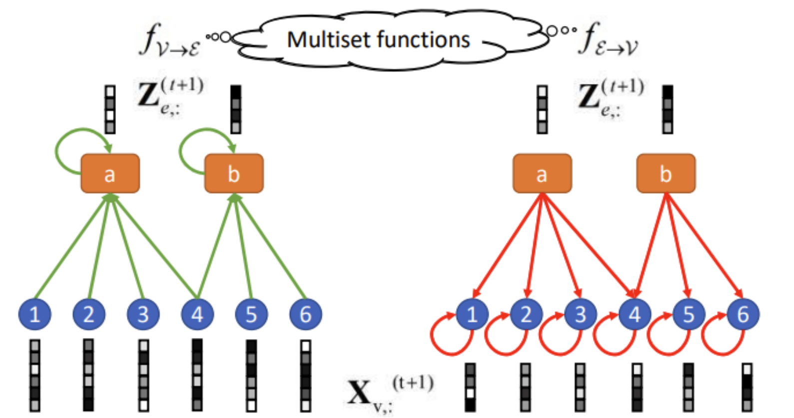
- A Convolution Layer:
  - First Update Hyperedge embedding:

$$\mathbf{Z}_{b,:}^{(t+1)} = f_{\mathcal{V}\to\mathcal{E}}(\{\mathbf{X}_{3,:}^{(t)}, \mathbf{X}_{4,:}^{(t)}, \mathbf{X}_{5,:}^{(t)}\}; \mathbf{Z}_{b,:}^{(t)})$$

  - Then learns node embedding:

$$\mathbf{X}_{4,:}^{(t+1)} = f_{\mathcal{E}\to\mathcal{V}}(\{\mathbf{Z}_{a,:}^{(t+1)}, \mathbf{Z}_{b,:}^{(t+1)}\}; \mathbf{X}_{4,:}^{(t)})$$





You are Allset: A Multiset Function Framework for Hypergraph Neural Networks. ICLR'22

In-Class Activity 2

- Convert hypergraphs into graphs via CE and SE.

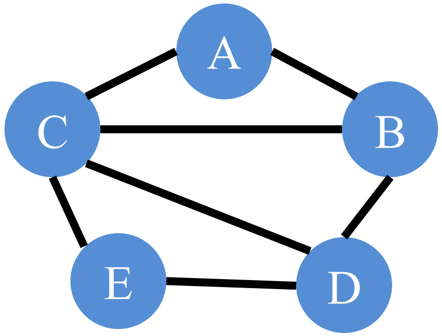
- Five authors (nodes) A, B, … E, and papers (hyperedges):
  - {A, B, C}
  - {B, D}
  - {C, D, E}

- What do the converted graphs look like?

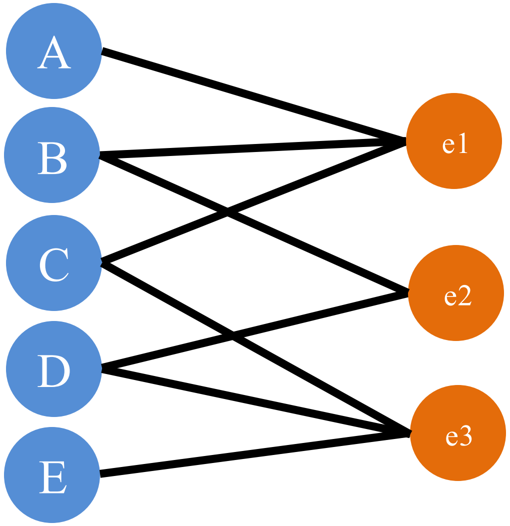
- What are the pros and cons of each method?

In-Class Activity 2

- Clique Expansion:



- Star Expansion:

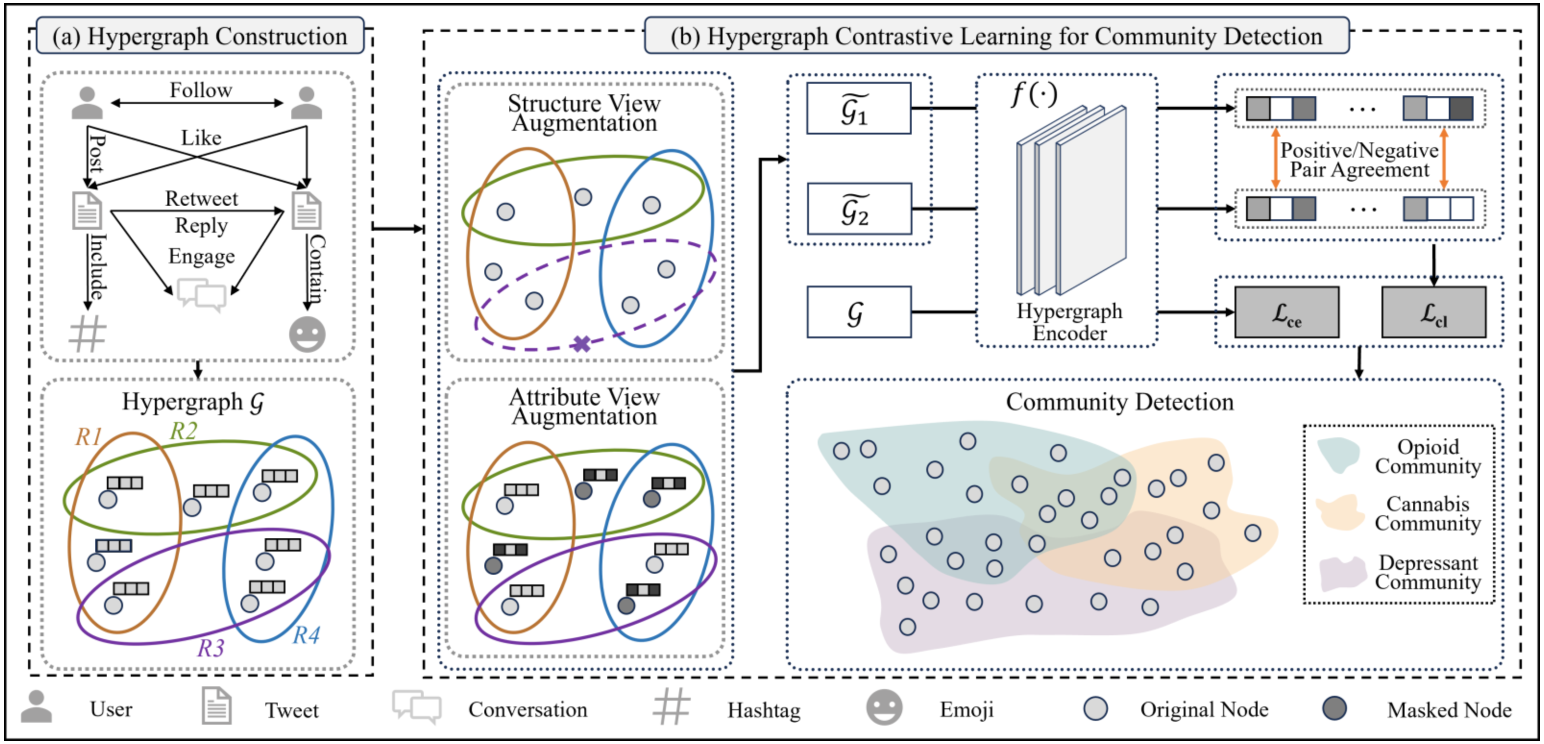


Only know the authors collaborated, but the “specific paper” information is lost.

Authors are not directly connected. 1-hop relationship => 2-hop relationship.

Applications

- Community Detection on Social Media



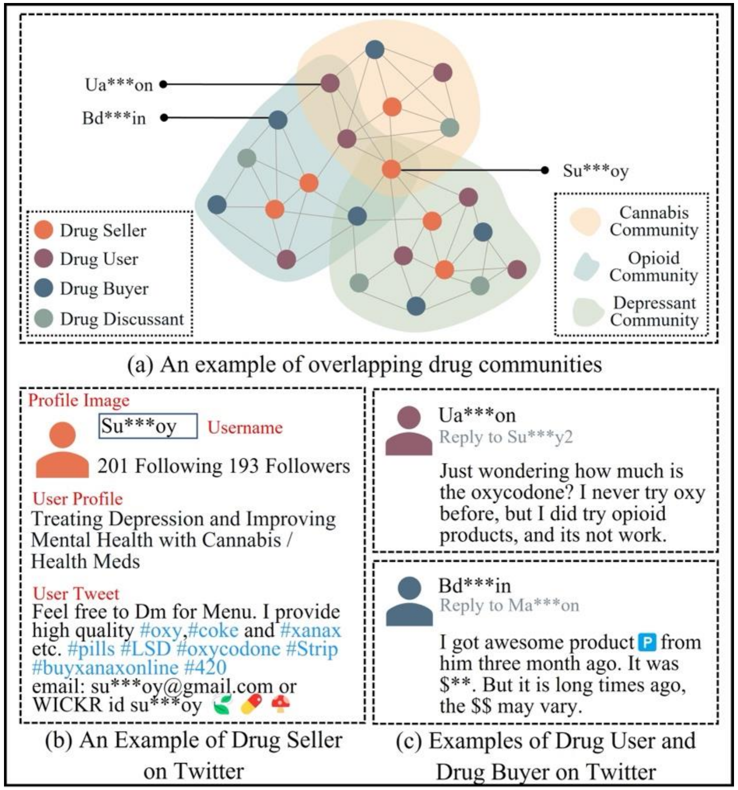
Hypergraph Contrastive Learning for Drug Trafficking Community Detection. ICDM'23

Background

Illicit drug trafficking markets remain highly profitable. The crime of drug trafficking has adapted and evolved with modern technologies.

Major social media platforms have become intermediaries for illicit drug trafficking.

These group-wise drug trafficking scenarios pose serious challenges to the public, which needs immediate action to address this issue.



Challenges & Solutions

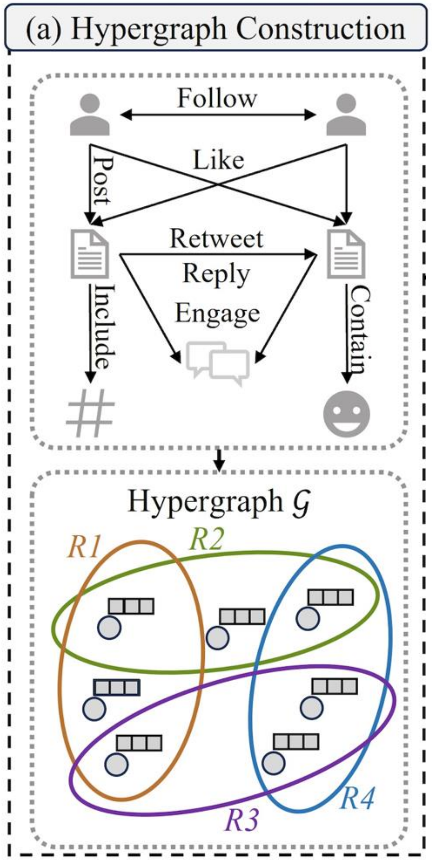
- Study drug trafficking by analyzing individual role from a single perspective.
- Study online drug communities that are involved with four types of roles
- Focus on pairwise relationships among users on social medial.
- Drug trafficking hypergraph Twitter-HyDrug and HyGNNs.
- Require sufficient labeled samples to train models.
- Hypergraph contrastive learning methods.

Drug Hypergraph Construction

- We concatenate the informative text content and leverage SentenceBert to convert it into a fixed-length feature vector (d=384) as attribute feature for the corresponding user node.

- We define four types of hyperedges to describe the activities among users within the hypergraph: *users-follow-user, users-engaged-conversation, users-included-hashtag, and users-contain-emoji.*

- To conclude, Twitter-HyDrug has 2,936 user nodes and 33,892 hyperedges. Twitter-HyDrug is available at https://github.com/GraphResearcher/HyGCL-DC.



Hypergraph Representation Learning

- This method is applicable to any HyGNNs, and in this work, we leverage a two-layer HyperGCN as an encoder example:

$$Z = \bar{A}^{(2)}\mathrm{ReLU}(\bar{A}^{(1)}\mathcal{X}W^{(1)})W^{(2)},$$

where $\bar{A}^{(1)}$ and $\bar{A}^{(2)}$ are weighted adjacency matrices generated by HyperGCN in the first and second layer, respectively. $W^{(1)}$ is the weight matrix in first layer and $W^{(2)}$ is the weight matrix for the second layer.

Hypergraph Contrastive Learning

- Structure view augmentation:

  $\tilde{\mathcal{E}} = \{e_i : \widetilde{\mathcal{M}}^s = 1, e_i \in \mathcal{E}\}$ with hyperedge masking matrix $\widetilde{\mathcal{M}}^s \in \{0,1\}^{1\times M} \sim \mathcal{B}(p_s)$.

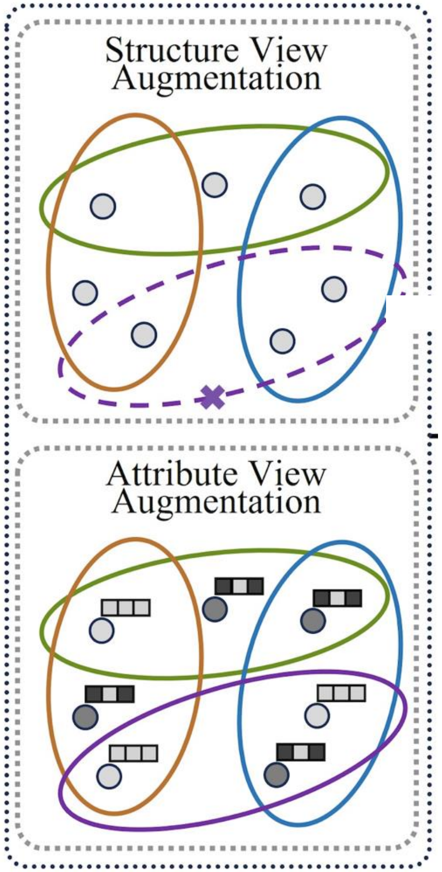
- Attribute view augmentation:

  $\widetilde{\mathcal{X}} = \{x_i \cdot \widetilde{\mathcal{M}}^a + \lambda_i : x_i \in \mathcal{X}\}$ with a node mask matrix $\widetilde{\mathcal{M}}^a \in \{0,1\}^{1\times N} \sim \mathcal{B}(p_a)$ and random noise λ .

- Contrastive optimization:

$$[\widetilde{\mathcal{G}_1}, \widetilde{\mathcal{G}_2}] = [(\mathcal{V}, \widetilde{\mathcal{E}_1}, \widetilde{\mathcal{X}_1}), (\mathcal{V}, \widetilde{\mathcal{E}_2}, \widetilde{\mathcal{X}_2})] \Rightarrow \text{ encoder f}(\cdot) \Rightarrow [\widetilde{Z_1}, \widetilde{Z_2}]$$

$$\mathcal{L}_{cl} = -\frac{1}{N}\log \sum_{v_i \in \mathcal{V}} \frac{\exp(\delta_{i,i}/\tau)}{\sum_{j\neq i}\exp(\delta_{i,j}/\tau) + \exp(\delta_{i,i}/\tau)}$$



Community Detection

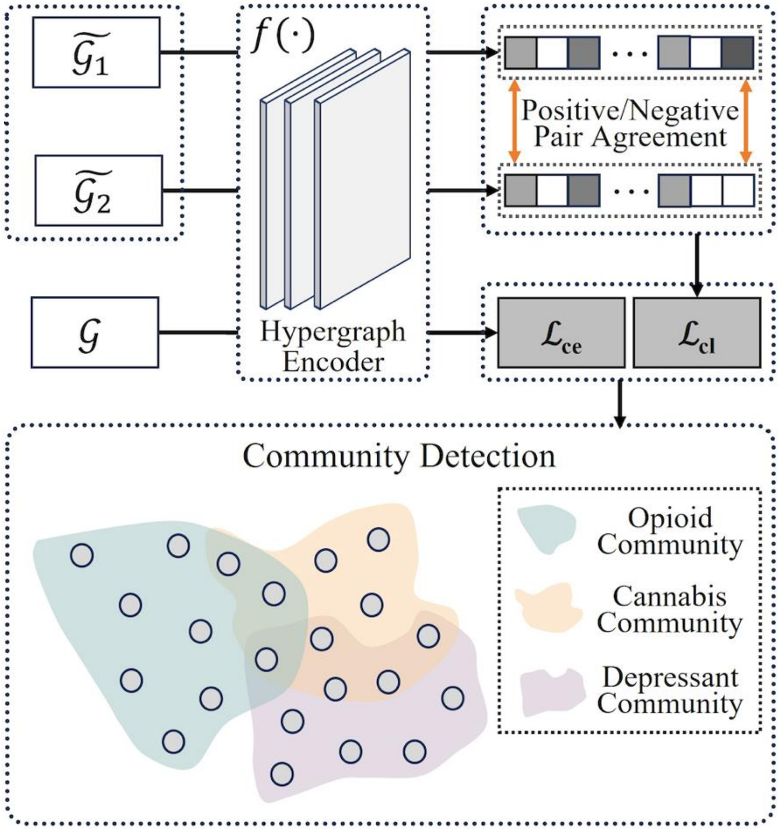
- We regard the drug trafficking community detection as a node classification task that aim to classify which communities each node should belong to.

- The node embeddings are fed into a classifier (MLPs) to get the probability distribution and employ the binary cross-entropy (BCE) loss as the community detection loss $\mathcal{L}_{ce}$.

- The final objective for community detection is:

$$\mathcal{L} = \alpha_1 \mathcal{L}_{ce} + \alpha_2 \mathcal{L}_{cl} \,,$$

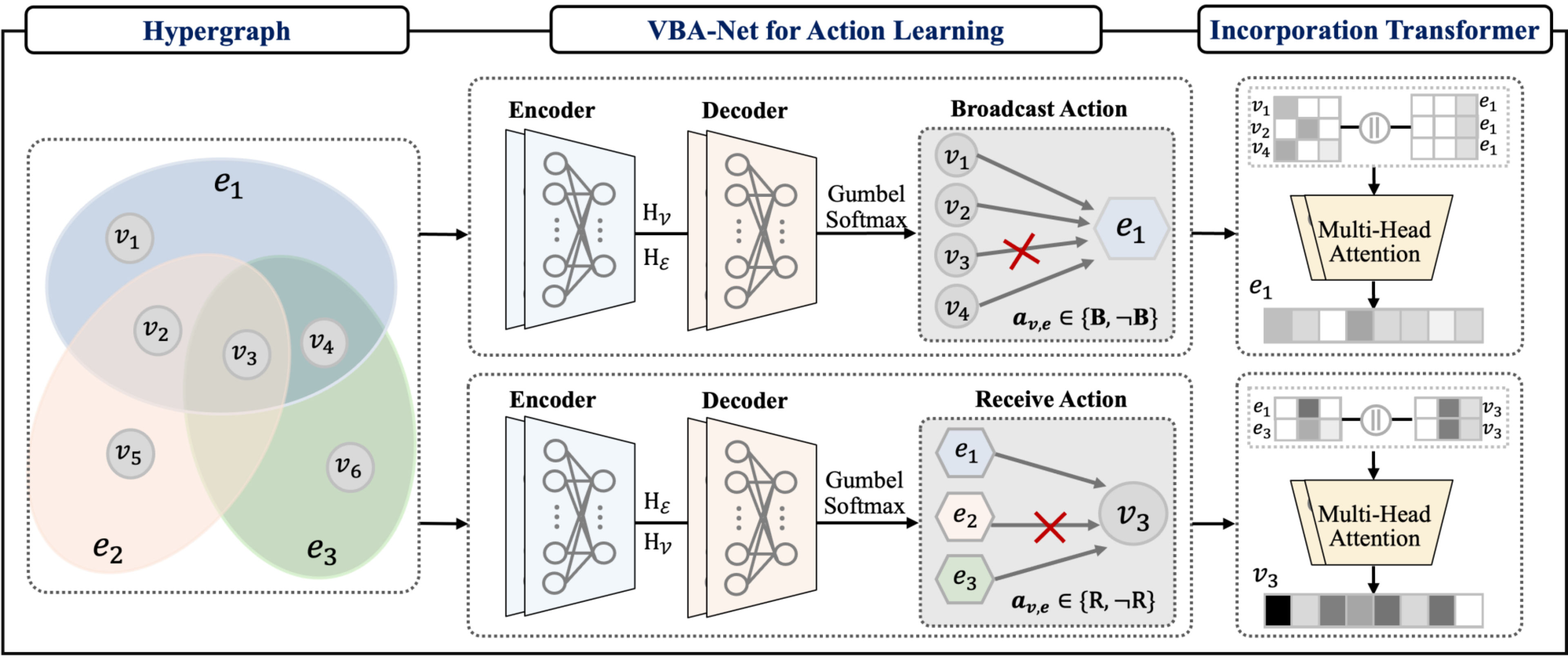
where α_1 and α_2 are the trade-off hyper-parameters.



Experiment and Analysis

Setting		Twitter-HyDrug		Cora-author		Cora-citation		Citeseer-citation	
Group	Model	Jaccard	F1-score	Jaccard	F1-score	Jaccard	F1-score	Jaccard	F1-score
G1	K-means [37]	15.43 ± 0.33	31.53 ± 2.05	12.15 ± 4.36	22.10 ± 5.68	18.36 ± 4.91	26.64 ± 5.68	15.38 ± 4.32	20.10 ± 3.28
	BigClam [38]	23.46 ± 2.54	36.74 ± 7.24	19.73 ± 4.93	27.71 ± 5.28	21.53 ± 5.28	28.54 ± 4.29	17.21 ± 4.15	20.45 ± 4.05
	CESNA [39]	37.26 ± 4.60	40.83 ± 3.45	21.81 ± 5.04	31.02 ± 4.19	20.41 ± 3.46	34.31 ± 3.72	20.94 ± 2.97	23.15 ± 2.84
G2	GCN [5]	44.56 ± 1.03	61.64 ± 1.00	42.73 ± 3.44	70.24 ± 5.41	47.83 ± 1.46	63.91 ± 2.61	47.83 ± 0.62	51.89 ± 0.78
	GAT [6]	48.65 ± 2.02	60.35 ± 1.39	51.73 ± 8.43	67.75 ± 7.99	45.92 ± 6.91	62.44 ± 8.12	23.14 ± 3.79	37.42 ± 5.18
	GIN [40]	45.07 ± 0.82	61.74 ± 0.82	59.69 ± 4.80	70.95 ± 3.75	57.56 ± 0.83	70.60 ± 0.69	48.20 ± 2.30	65.02 ± 2.08
G3	CLARE [13]	50.17 ± 3.06	64.55 ± 3.95	54.19 ± 8.19	71.34 ± 5.26	55.26 ± 4.12	70.83 ± 3.19	48.70 ± 1.23	62.12 ± 2.67
	SEAL [12]	40.24 ± 2.37	58.92 ± 2.19	48.96 ± 6.48	60.07 ± 4.43	50.25 ± 5.10	65.26 ± 4.43	38.26 ± 1.37	56.45 ± 3.71
	Bespoke [41]	41.68 ± 3.74	59.02 ± 1.14	50.30 ± 6.25	63.19 ± 4.21	48.02 ± 3.17	64.89 ± 5.13	36.90 ± 2.93	51.64 ± 3.04
G4	HyperGCN [21]	56.83 ± 2.38	72.45 ± 1.93	66.15 ± 0.89	79.62 ± 0.64	62.86 ± 1.46	77.19 ± 1.11	55.15 ± 3.13	71.06 ± 2.58
	HGNN [20]	55.45 ± 0.44	72.16 ± 1.42	65.96 ± 0.74	79.54 ± 1.46	60.13 ± 2.14	76.39 ± 2.18	54.27 ± 1.47	68.59 ± 0.75
	HCHA [42]	52.78 ± 1.42	65.83 ± 1.42	58.84 ± 2.07	75.43 ± 1.60	56.29 ± 0.97	73.41 ± 1.81	52.89 ± 2.45	64.53 ± 1.89
Ours	**HyGCL-DC**	60.05 ± 0.54	74.85 ± 2.15	68.67 ± 0.94	81.20 ± 1.02	64.73 ± 0.14	78.59 ± 0.11	56.72 ± 2.85	72.36 ± 2.30

Representation Learning for Heterophilic



Hypergraph Representation Learning with Adaptive Broadcasting and Receiving. ICDM’25

ICDM 2025 Best Paper Award Candidate

Background

- Hypergraph Homophily Score

Given a hypergraph $\mathcal{H} = (\mathcal{V}, \mathcal{E})$, with a set of node classes $\mathcal{C} = \{c_1, \dots, c_{|\mathcal{C}|}\}$:

Homophily Score for node v is

$$h(v) = \frac{|\{ u: u \in \mathcal{N}(v),\ y_v = y_u \}|}{|\mathcal{N}(v)|}.$$

$\mathcal{N}(v)$ is the neighbor of v.

Homophily Score for hyperedge e:

$$h(e) = \max_{c \in \mathcal{C}} \frac{|\{ v: v \in e, y_v = c \}|}{|e|}.$$

Challenges

- Heterophilic Hypergraph

Connected nodes belong to different classes.

  – HyGNNs are designed based on high homophily assumption.

Hypergraph Neural Networks (HyGNNs)

  – MLPs outperform HyGNNs in modeling heterophilic hypergraphs.

	SENATE		SYNTHETIC		CONGRESS		HOUSE		WALMART	
MLP [52]	$62.24_{\pm6.39}$	$50.35_{\pm3.25}$	$50.00_{\pm1.19}$	$37.48_{\pm0.65}$	$79.45_{\pm1.18}$	$65.91_{\pm1.55}$	$77.12_{\pm3.00}$	$64.07_{\pm2.70}$	$62.23_{\pm0.14}$	$44.69_{\pm0.13}$
HGNN [10]	$60.06_{\pm2.81}$	$49.35_{\pm2.64}$	$42.42_{\pm1.85}$	$37.90_{\pm1.54}$	$90.91_{\pm0.77}$	$88.08_{\pm1.37}$	$61.24_{\pm1.72}$	$57.24_{\pm1.76}$	$77.19_{\pm0.12}$	$61.34_{\pm0.19}$
HyperGCN [11]	$55.00_{\pm3.02}$	$51.82_{\pm2.49}$	$41.61_{\pm2.03}$	$32.51_{\pm1.24}$	$84.81_{\pm1.56}$	$83.32_{\pm1.18}$	$75.62_{\pm2.03}$	$62.43_{\pm2.68}$	$62.02_{\pm0.67}$	$49.61_{\pm0.42}$
HNHN [12]	$62.18_{\pm6.99}$	$54.71_{\pm4.15}$	$49.67_{\pm1.45}$	$37.11_{\pm0.93}$	$89.71_{\pm1.17}$	$82.97_{\pm1.66}$	$68.36_{\pm2.21}$	$65.16_{\pm1.88}$	$68.68_{\pm0.95}$	$58.01_{\pm0.46}$
HCHA [23]	$47.71_{\pm1.37}$	$46.20_{\pm2.84}$	$32.50_{\pm1.73}$	$27.18_{\pm1.44}$	$91.04_{\pm0.64}$	$89.81_{\pm0.91}$	$61.28_{\pm1.54}$	$56.98_{\pm1.42}$	$76.55_{\pm0.15}$	$61.83_{\pm0.19}$
UniGCNII [53]	$60.06_{\pm5.16}$	$52.24_{\pm4.17}$	$49.62_{\pm1.37}$	$37.13_{\pm1.40}$	$92.91_{\pm1.04}$	$89.56_{\pm6.48}$	$78.64_{\pm1.29}$	$65.45_{\pm1.36}$	$72.36_{\pm1.26}$	$63.72_{\pm0.52}$

VBA-Net for Action Learning

- Nodes take action a, *i.e.*, ***broadcast*** ($\mathbf{B}$) and ***receive*** ($\boldsymbol{R}$), to learn valuable information.

- Motivation: Users in social media
  - Users (nodes) broadcast/receive ideas from topics (hyperedges).
  - Prioritize on their interested topics.
  - Topic representations are from broadcast ideas.
  - User representations learns from the received topics.

VBA-Net for Action Learning

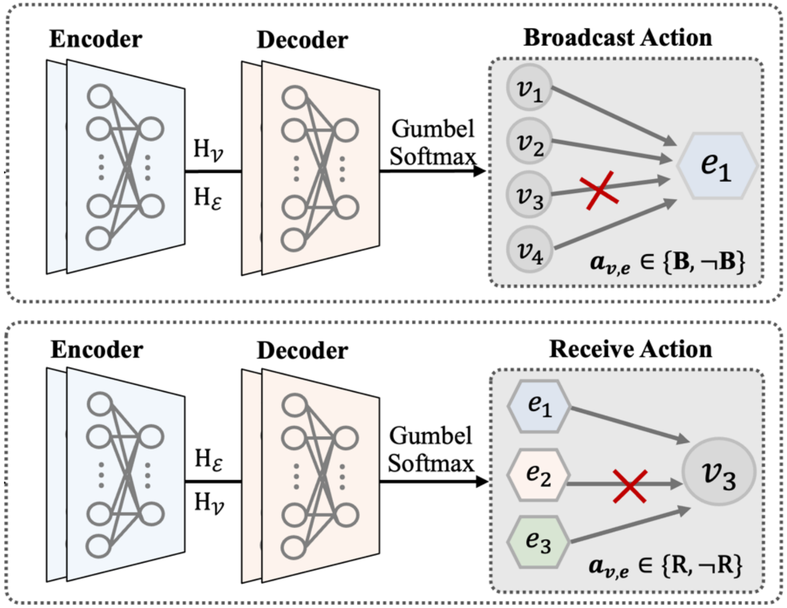
- VBA-Net, Variational **B**roadcast **A**utoencoder **Net**work

- Encoder:

$$\mathbf{H}_* \sim q(\mathbf{H}_* | \mathcal{H}) = \mathcal{N}(\mu_*, \sigma_*^2), \text{ where}$$
$$\mu_\mathcal{V} = \mathrm{MLP}_\mathcal{V}^{(\mu)}(Z_\mathcal{V}),\ \log\sigma_\mathcal{V} = \mathrm{MLP}_\mathcal{V}^{(\sigma)}(Z_\mathcal{V}),$$
$$\mu_\mathcal{E} = \mathrm{MLP}_\mathcal{E}^{(\mu)}(Z_\mathcal{E}),\ \log\sigma_\mathcal{E} = \mathrm{MLP}_\mathcal{E}^{(\sigma)}(Z_\mathcal{E}).$$

$*$ denotes either $\mathcal{V}$ or $\mathcal{E}$.

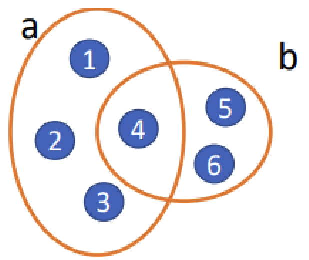
- Decoder:



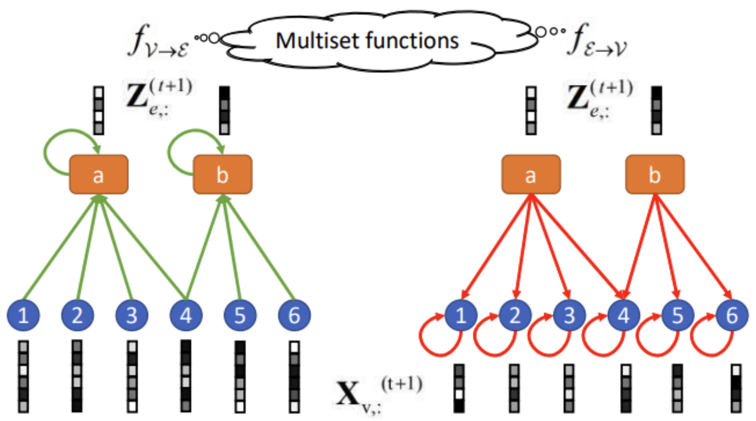
$$\boldsymbol{a} = \mathrm{Gumbel\_Softmax}(p), \text{where } p = \mathrm{P}(a\,|\mathrm{H}_\mathcal{V}, \mathrm{H}_\mathcal{E}),$$
$$\mathrm{H}_\mathcal{V} = \rho_\mathcal{V} \odot \sigma_\mathcal{V} + \mu_\mathcal{V}, \text{and } \mathrm{H}_e = \rho_\mathcal{E} \odot \sigma_\mathcal{E} + \mu_\mathcal{E}.$$

Incorporation Transformer

- Existing works hard to distinguish nodes from distinct classes.



Given two nodes v_1 and v_2, from distinct classes,
If $\{e, \forall e \in \mathcal{E}, v_1 \in e\} = \{e, \forall e \in \mathcal{E}, v_2 \in e\}$
Then $\mathbf{Z}_{v_1} = \mathbf{Z}_{v_2}$.



Incorporation Transformer (Cont'd)

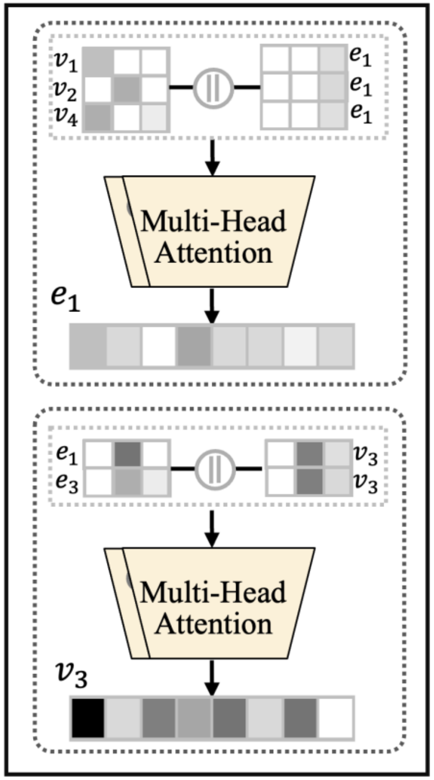
- Incorporate both side (node/hyperege) information to update target side representations

$$\mathrm{Z}_e = \mathrm{MH}\left(\mathrm{S}_e^{(\mathrm{B})}; \theta_e\right), \text{and } \mathrm{Z}_v = \mathrm{MH}\left(\mathrm{S}_v^{(\mathrm{R})}; \theta_v\right), \text{where}$$

$$\mathrm{S}_e^{(\mathrm{B})} = \begin{bmatrix} \mathcal{Z}_{e,1}^{(\mathrm{B})} \\ \cdots \\ \mathcal{Z}_{e,c_e}^{(\mathrm{B})} \end{bmatrix}, \mathcal{Z}_e^{(\mathrm{B})} = \{Z_v' | Z_e' : a_{v,e}^{(\mathrm{B})} = \mathbf{B}\}, c_e = \left|\mathcal{Z}_e^{(\mathrm{B})}\right|,$$

$$\mathrm{S}_v^{(\mathrm{R})} = \begin{bmatrix} \mathcal{Z}_{v,1}^{(\mathrm{R})} \\ \cdots \\ \mathcal{Z}_{v,c_v}^{(\mathrm{B})} \end{bmatrix}, \mathcal{Z}_v^{(\mathrm{R})} = \{Z_e | Z_v' : a_{e,a}^{(\mathrm{B})} = \mathbf{R}\}, c_v = \left|\mathcal{Z}_v^{(\mathrm{R})}\right|,$$

Multi-head Attention $\mathrm{MH}(\mathrm{S}; \theta) = ||_{i=1}^{h} \mathrm{O}^i, \mathrm{O}^i = \omega(\theta^i (\mathrm{K}^i)^{\mathrm{T}}$.



Objective Function

- The variational lower bound loss for VBA-Net

$$\mathcal{L}_{\mathrm{vlb}}^{(*)} = \mathbb{E}_{q(\mathrm{H}_{\mathcal{V}}|\mathcal{H})}\mathbb{E}_{q(\mathrm{H}_{\mathcal{E}}|\mathcal{H})}[\log \mathrm{P}(*\,|\mathrm{H}_{\mathcal{V}}, \mathrm{H}_{\mathcal{E}})]$$
$$-D_{KL}[q(\mathrm{H}_{\mathcal{V}}|\mathcal{H})|p(\mathrm{H}_{\mathcal{V}})] - D_{KL}[q(\mathrm{H}_{\mathcal{E}}|\mathcal{H})|p(\mathrm{H}_{\mathcal{E}})].$$

- The variational loss for the l-th layer

$$\mathcal{L}_{\mathrm{vlb}}^{(*)} = \mathbb{E}_{q(\mathrm{H}_{\mathcal{V}}|\mathcal{H})}\mathbb{E}_{q(\mathrm{H}_{\mathcal{E}}|\mathcal{H})}[\log \mathrm{P}(*\,|\mathrm{H}_{\mathcal{V}}, \mathrm{H}_{\mathcal{E}})]$$
$$-D_{KL}[q(\mathrm{H}_{\mathcal{V}}|\mathcal{H})|p(\mathrm{H}_{\mathcal{V}})] - D_{KL}[q(\mathrm{H}_{\mathcal{E}}|\mathcal{H})|p(\mathrm{H}_{\mathcal{E}})].$$

- Overall optimization objective

$$\mathcal{L}_{\mathrm{total}} = \mathcal{L}_{\mathrm{ce}} + \sum_{l=1}^{L} \mathcal{L}_{\mathrm{var.}}^{(l)}$$

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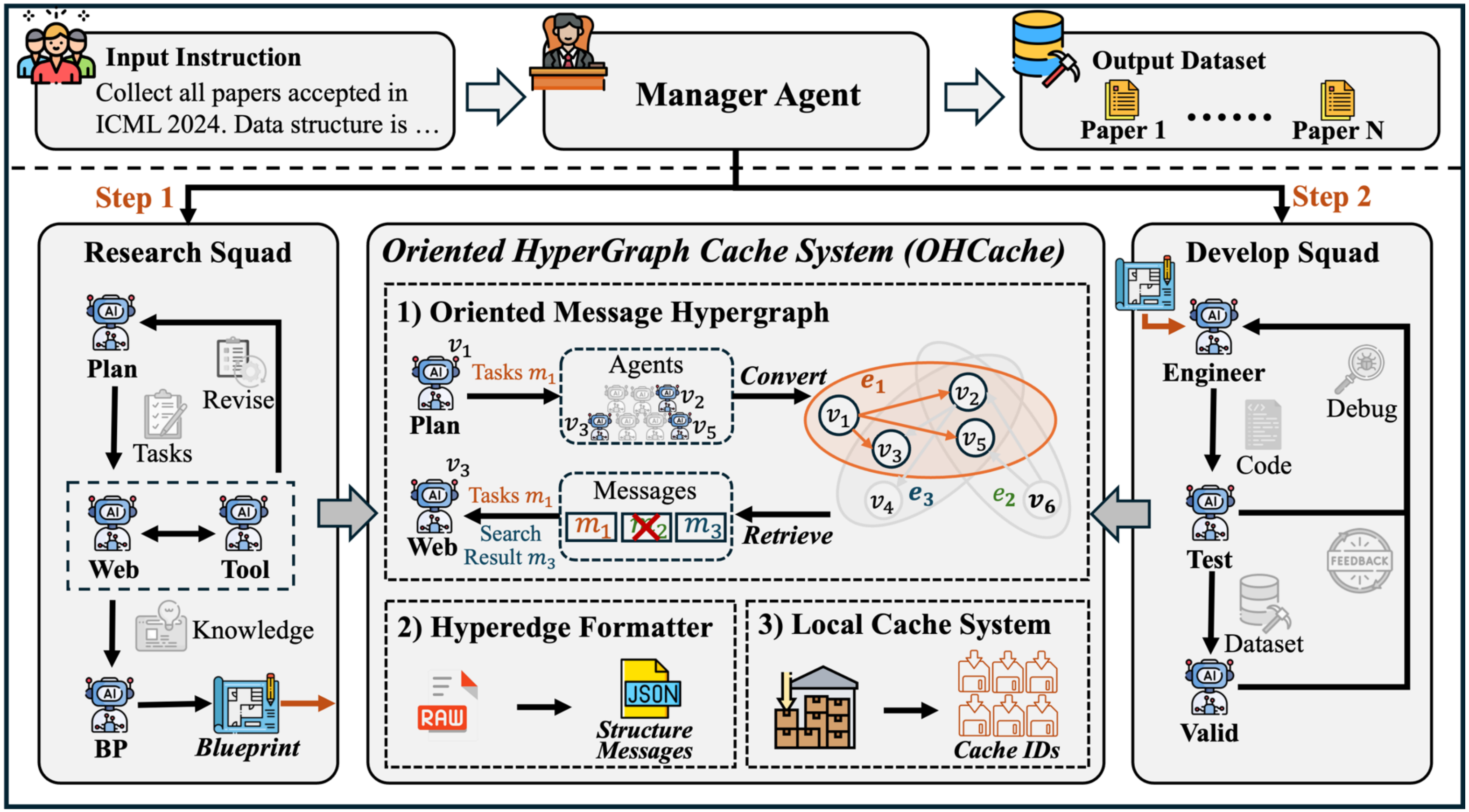
Experiment Analysis (Het.)

	Senate		Synthetic		Congress		House		Walmart	
# Nodes	282	282	2,000	2,000	1,718	1,718	1,290	1,290	88,860	88,860
# Edges	315	315	1,000	1,000	83,105	83,105	340	340	69,906	69,906
Avg. $h(v)$	0.50	0.50	0.28	0.28	0.55	0.55	0.51	0.51	0.53	0.53
Avg. $h(e)$	0.55	0.55	0.33	0.33	0.79	0.79	0.58	0.58	0.75	0.75
Noise std σ	0.6	1.0	0.6	1.0	0.6	1.0	0.6	1.0	0.6	1.0
MLP [52]	$62.24_{\pm 6.39}$	$50.35_{\pm 3.25}$	$50.00_{\pm 1.19}$	$37.48_{\pm 0.65}$	$79.45_{\pm 1.18}$	$65.91_{\pm 1.55}$	$77.12_{\pm 3.00}$	$64.07_{\pm 2.70}$	$62.23_{\pm 0.14}$	$44.69_{\pm 0.13}$
HGNN [10]	$60.06_{\pm 2.81}$	$49.35_{\pm 2.64}$	$42.42_{\pm 1.85}$	$37.90_{\pm 1.54}$	$90.91_{\pm 0.77}$	$88.08_{\pm 1.37}$	$61.24_{\pm 1.72}$	$57.24_{\pm 1.76}$	$77.19_{\pm 0.12}$	$61.34_{\pm 0.19}$
HyperGCN [11]	$55.00_{\pm 3.02}$	$51.82_{\pm 2.49}$	$41.61_{\pm 2.03}$	$32.51_{\pm 1.24}$	$84.81_{\pm 1.56}$	$83.32_{\pm 1.18}$	$75.62_{\pm 2.03}$	$62.43_{\pm 2.68}$	$62.02_{\pm 0.67}$	$49.61_{\pm 0.42}$
HNHN [12]	$62.18_{\pm 6.99}$	$54.71_{\pm 4.15}$	$49.67_{\pm 1.45}$	$37.11_{\pm 0.93}$	$89.71_{\pm 1.17}$	$82.97_{\pm 1.66}$	$68.36_{\pm 2.21}$	$65.16_{\pm 1.88}$	$68.68_{\pm 0.95}$	$58.01_{\pm 0.46}$
HCHA [23]	$47.71_{\pm 1.37}$	$46.20_{\pm 2.84}$	$32.50_{\pm 1.73}$	$27.18_{\pm 1.44}$	$91.04_{\pm 0.64}$	$89.81_{\pm 0.91}$	$61.28_{\pm 1.54}$	$56.98_{\pm 1.42}$	$76.55_{\pm 0.15}$	$61.83_{\pm 0.19}$
UniGCNII [53]	$60.06_{\pm 5.16}$	$52.24_{\pm 4.17}$	$49.62_{\pm 1.37}$	$37.13_{\pm 1.40}$	$92.91_{\pm 1.04}$	$89.56_{\pm 6.48}$	$78.64_{\pm 1.29}$	$65.45_{\pm 1.36}$	$72.36_{\pm 1.26}$	$63.72_{\pm 0.52}$
AllSet [26]	$65.47_{\pm 3.42}$	$51.76_{\pm 4.60}$	$52.84_{\pm 0.80}$	$42.78_{\pm 0.81}$	$93.65_{\pm 1.29}$	$88.65_{\pm 3.84}$	$78.81_{\pm 1.51}$	$65.20_{\pm 1.58}$	$78.74_{\pm 0.25}$	$65.35_{\pm 0.25}$
ED-HNN [19]	$65.53_{\pm 3.10}$	$55.47_{\pm 4.87}$	$55.96_{\pm 1.34}$	$43.59_{\pm 1.54}$	$94.20_{\pm 0.98}$	$92.07_{\pm 0.75}$	$79.01_{\pm 1.00}$	$65.70_{\pm 1.98}$	$78.15_{\pm 0.42}$	$65.07_{\pm 0.84}$
HyGCL-ADT [54]	$64.85_{\pm 3.37}$	$52.93_{\pm 2.94}$	$55.92_{\pm 2.16}$	$42.31_{\pm 1.63}$	$93.10_{\pm 2.37}$	$91.86_{\pm 2.49}$	$79.43_{\pm 1.30}$	$64.72_{\pm 1.92}$	$78.41_{\pm 0.51}$	$65.34_{\pm 0.86}$
SheafHGNN [55]	$64.35_{\pm 4.72}$	$54.32_{\pm 4.26}$	$55.42_{\pm 3.82}$	$43.97_{\pm 2.73}$	$90.72_{\pm 2.41}$	$91.07_{\pm 2.97}$	$79.75_{\pm 1.84}$	$65.93_{\pm 2.30}$	OOM	OOM
HypeBoy [56]	$63.47_{\pm 3.62}$	$53.17_{\pm 3.06}$	$53.74_{\pm 1.85}$	$42.26_{\pm 2.39}$	$92.34_{\pm 1.24}$	$90.52_{\pm 2.58}$	$79.32_{\pm 1.73}$	$65.35_{\pm 2.94}$	$76.42_{\pm 0.59}$	$64.28_{\pm 0.95}$
Ours	$\mathbf{67.87}_{\pm 2.13}$	$\mathbf{58.41}_{\pm 3.11}$	$\mathbf{58.10}_{\pm 1.44}$	$\mathbf{47.32}_{\pm 2.29}$	$\mathbf{95.45}_{\pm 0.62}$	$\mathbf{93.72}_{\pm 0.86}$	$\mathbf{80.23}_{\pm 1.31}$	$\mathbf{67.36}_{\pm 2.14}$	$\mathbf{79.94}_{\pm 1.31}$	$\mathbf{66.85}_{\pm 1.04}$

Experiment Analysis (Homo.)

	TWITTER		CITESEER		DBLP		CORA		CORA-CA		PUBMED	
# Nodes	2,936	2,936	3,312	3,312	41,302	41,302	2,708	2,708	2,708	2,708	19,717	19,717
# Edges	35,502	35,502	1,070	1,079	22,363	22,363	1,072	1,072	1,579	1,579	7,963	7,963
Avg. $h(v)$	0.41	0.82	0.42	0.83	0.49	0.87	0.40	0.80	0.45	0.90	0.48	0.95
Avg. $h(e)$	0.45	0.90	0.42	0.83	0.47	0.93	0.44	0.88	0.43	0.86	0.44	0.88
Type	HET.	HOMO.	HET.	HOMO.	HET.	HOMO.	HET.	HOMO.	HET.	HOMO.	HET.	HOMO.
MLP [52]	67.38±0.64	67.38±0.64	68.05±1.17	68.05±1.17	83.76±0.19	83.76±0.19	68.45±0.78	68.45±0.78	69.45±0.97	69.45±0.97	84.45±0.31	84.45±0.31
HGNN [10]	67.17±0.73	68.52±1.16	55.10±0.79	69.32±0.50	68.53±0.19	90.38±0.18	58.64±0.85	76.11±0.85	62.94±0.97	79.42±0.80	80.91±0.30	85.82±1.08
HyperGCN [11]	55.68±3.61	69.29±0.62	56.87±1.32	69.13±1.42	65.80±4.31	88.37±0.20	56.41±1.79	73.89±1.16	56.59±1.77	75.12±1.40	64.96±2.12	86.31±3.52
HNHN [12]	62.08±2.33	67.78±0.80	66.65±0.76	68.36±1.24	81.76±0.32	86.42±0.20	62.79±1.18	71.52±1.47	64.69±1.91	72.12±1.36	83.62±0.33	85.92±0.60
HCHA [23]	67.63±1.17	72.04±0.66	53.33±0.88	68.84±1.12	67.91±0.23	90.27±0.19	55.71±1.21	75.97±0.90	63.27±1.05	79.23±0.52	75.87±0.32	83.53±0.35
UniGCNII [53]	67.66±0.93	69.57±1.39	60.38±1.21	70.21±0.97	81.80±0.30	90.53±0.17	58.08±1.44	76.25±1.53	61.66±1.70	78.20±1.64	85.24±0.38	86.31±0.20
AllSet [26]	69.16±0.97	70.64±1.16	67.91±2.17	69.71±1.00	84.06±0.21	90.69±0.12	67.54±0.91	74.26±0.76	69.90±1.19	78.30±1.50	85.04±0.36	86.38±0.37
ED-HNN [19]	69.07±1.07	73.47±0.63	66.30±0.75	69.82±2.77	83.90±0.25	90.85±0.21	67.13±1.16	75.78±1.26	70.04±1.78	79.88±0.61	86.04±0.46	87.26±0.24
HyGCL-ADT [54]	70.08±1.28	72.46±2.56	66.51±1.83	**71.03±2.74**	83.76±0.69	90.56±0.26	67.01±1.77	76.35±0.82	69.72±2.41	80.52±1.52	85.73±1.05	86.89±0.51
SheafHGNN [55]	68.95±1.43	72.87±1.90	66.16±2.86	70.57±1.98	82.17±0.46	90.29±0.27	67.42±2.38	76.19±1.61	69.82±0.98	**81.14±2.38**	84.16±1.20	85.41±0.68
HypeBoy [56]	68.77±1.41	71.36±1.29	67.05±1.42	70.98±1.94	81.72±1.94	**91.26±0.84**	66.82±2.97	**76.40±1.37**	68.39±1.49	80.04±3.52	85.29±2.85	87.94±1.01
Ours	**72.86±0.94**	**75.61±0.76**	**68.95±1.60**	70.12±1.12	**85.05±0.25**	90.93±0.31	**69.26±1.04**	75.87±0.70	**70.99±1.55**	80.72±0.58	**86.90±0.39**	**88.02±0.53**

Beyond Representation Learning



AutoData: A Multi-Agent System for Open Web Data Collection. NeurIPS'25

Please read our paper if you are interested!

Conclusion

- Hypergraphs are crucial to model structure data.
- It has been widely used in real-world problems:
  - Community Detection
  - Social Media
  - …
- Hypergraph learning remains an active topic with several open questions:
  - Learn patterns beyond message-passing
  - Modeling hypergraphs with limited labels