Disentangling Degree-Related Biases and Interest for Out-Of-Distribution Generalized Directed Network Embedding

THE WEB CONFERENCE ACM

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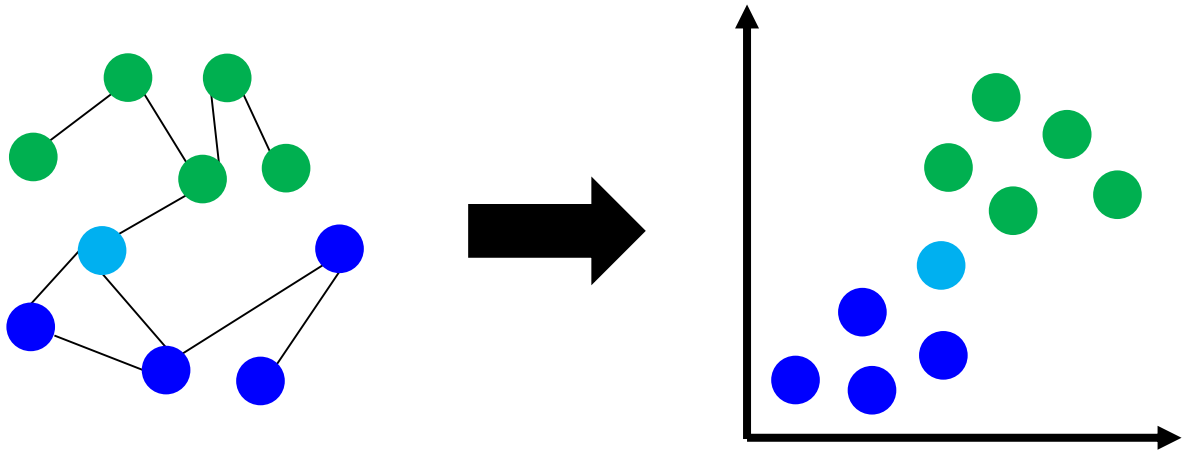
Background: Network Embedding (NE)

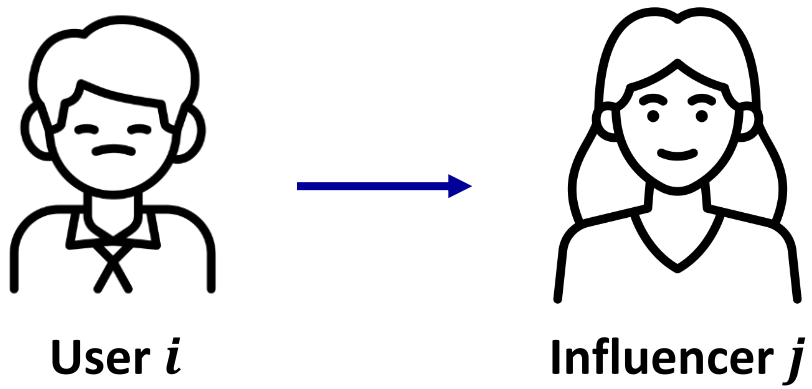
- **Represents nodes in a given network as low-dimensional vectors that preserve the structural properties of the network**
  - *e.g.*, proximity between nodes



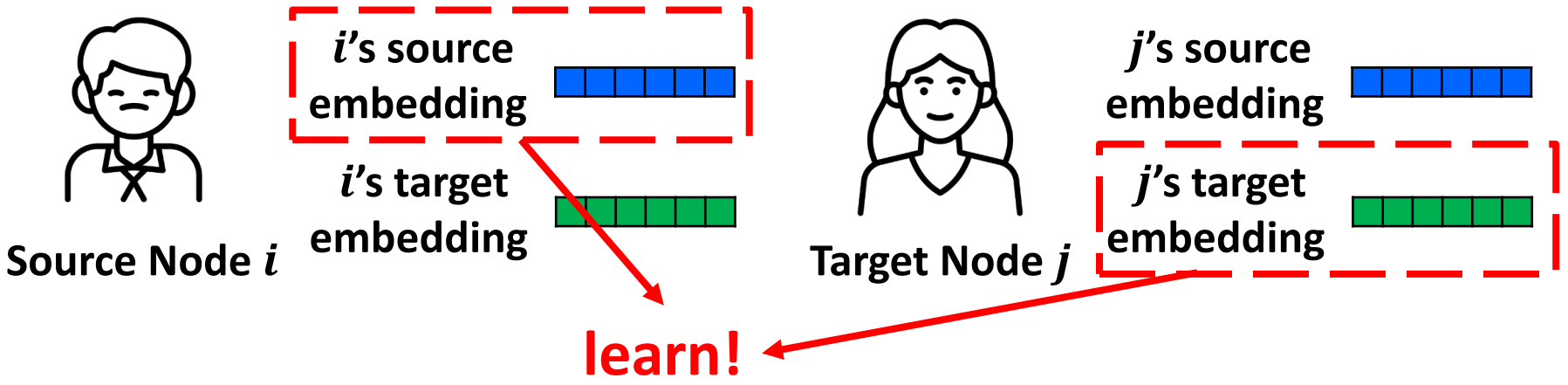
- **The learned embeddings can be used as informative features of nodes in various downstream tasks**
  - **Link prediction → our focus!**
  - Node clustering/classification
  - Recommendation

Background: Directed Network

- **Given a directed edge from i to j,**



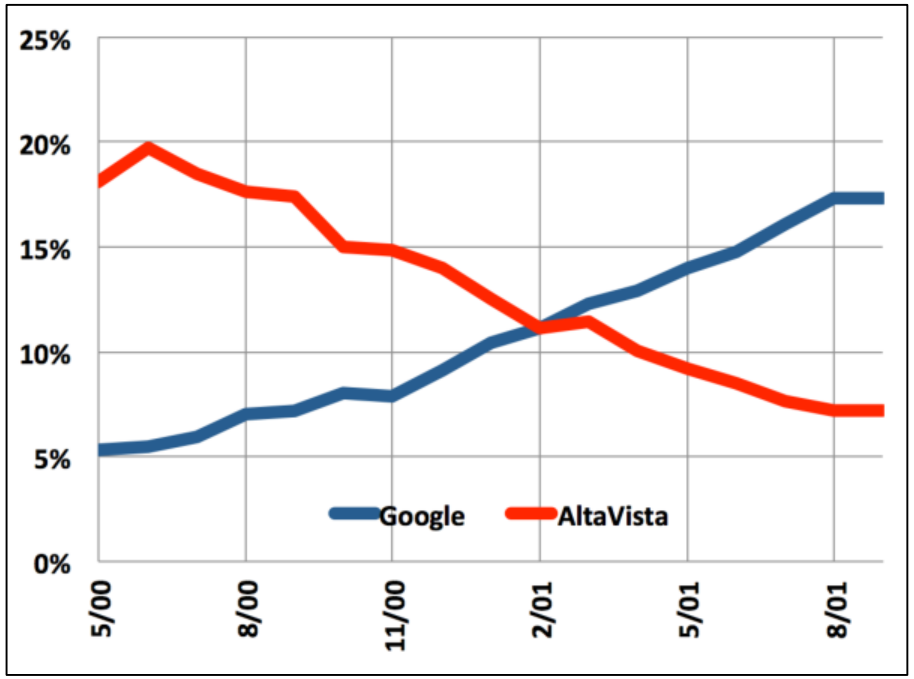
- Distinguish source node i and target node j according to their roles
- Learn a source embedding and a target embedding, which preserve the node's properties as sources and targets



Motivation

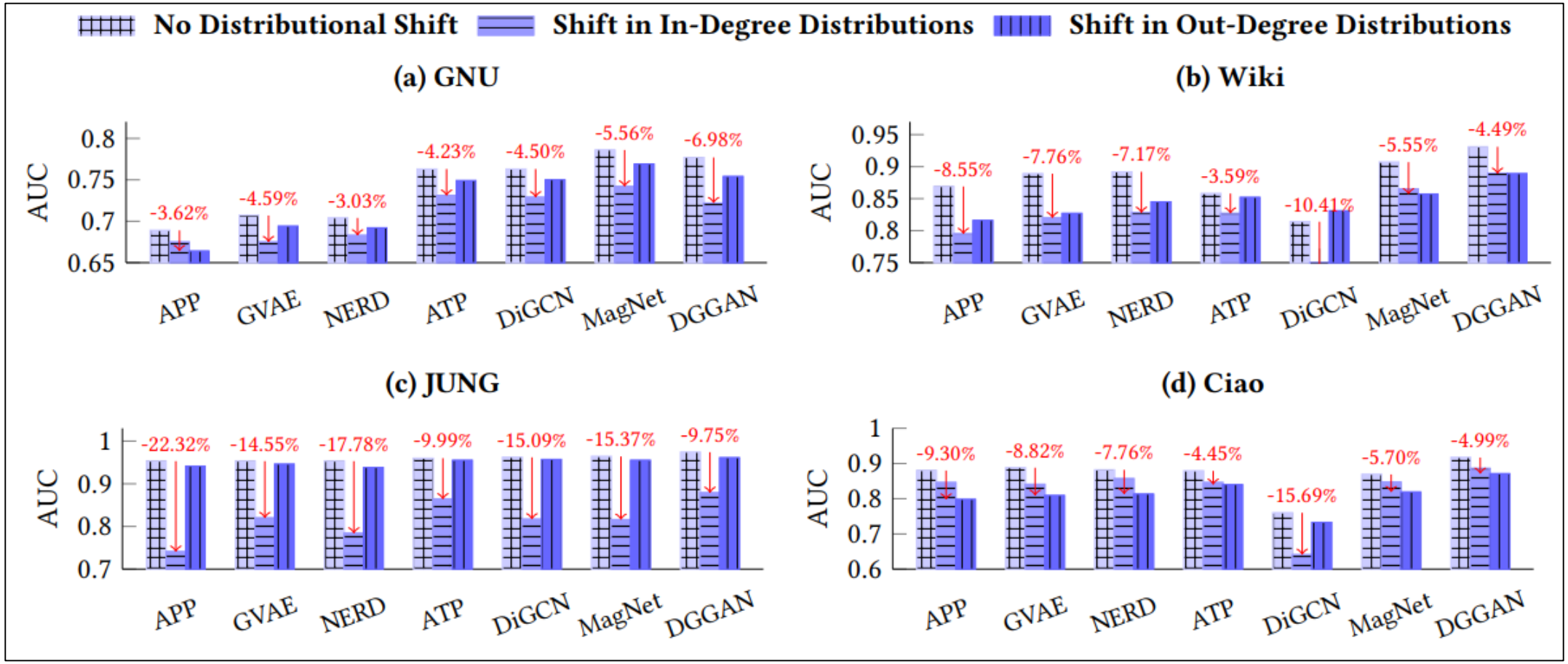
- **Existing DNE methods lack out-of-distribution (OOD) generalization abilities against degree-related distributional shifts**
  - They assume that, in link prediction, the degree distribution of the training and test data are identical (i.e., identical distribution)
- **However, degree-related distributional shifts occur frequently**
  - Fitness model: it is also common that dominant hubs are overtaken by "new kids on the block" with higher fitness

Ruining the identical distribution (ID) assumption!



Motivation (cont'd)

- **Link prediction accuracy of the existing methods in ID / non-ID settings**
  - The accuracies of all methods significantly degrade in the non-ID settings compared to the ID settings

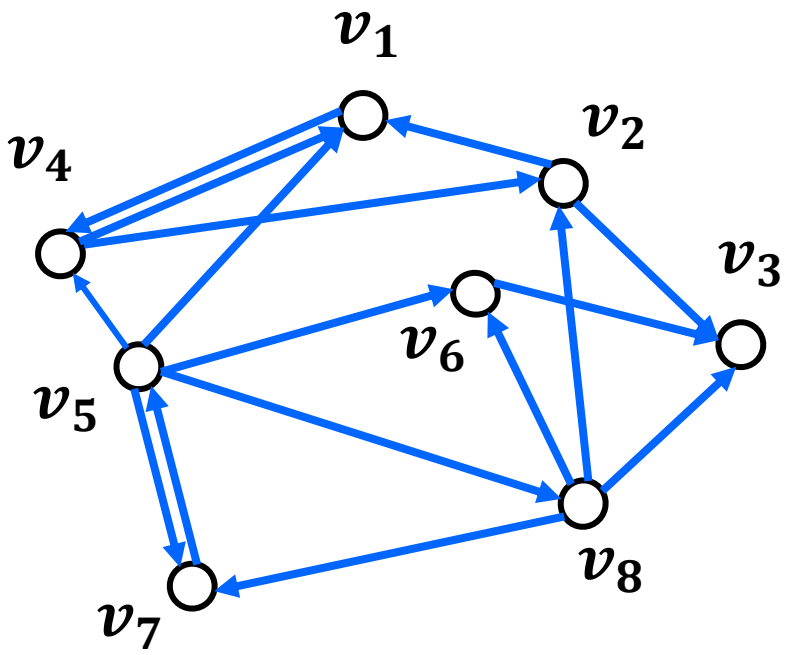


Proposed Method

- **Our idea: model and exploit biases related to node degrees for robustness against degree-related distributional shifts in DNE**

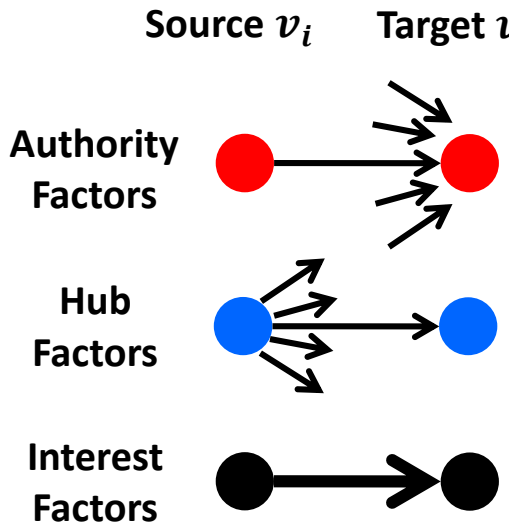
- **Propose ODIN (Out-of-Distribution Generalized Directed Network Embedding), which is designed to answer the following questions:**
  1. *How to model the formation of each directed edge?*
     - Define six node factors that can influence the formation of a directed edge from source to target
  2. *How to leverage such modeled factors for learning OOD generalized embeddings?*
     - Learn multiple factor embeddings, each of which preserves its desired factor

Overview of ODIN

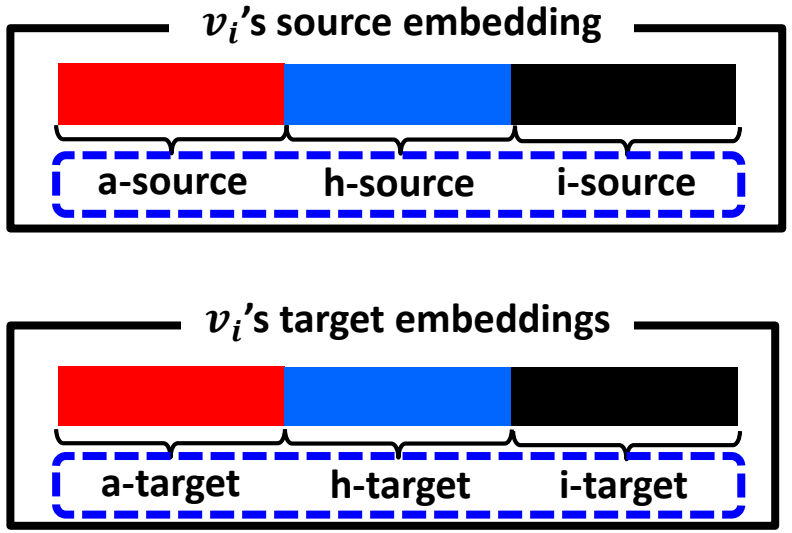


Directed Network $\mathcal{G}$

(STAGE 1) Factor Modeling



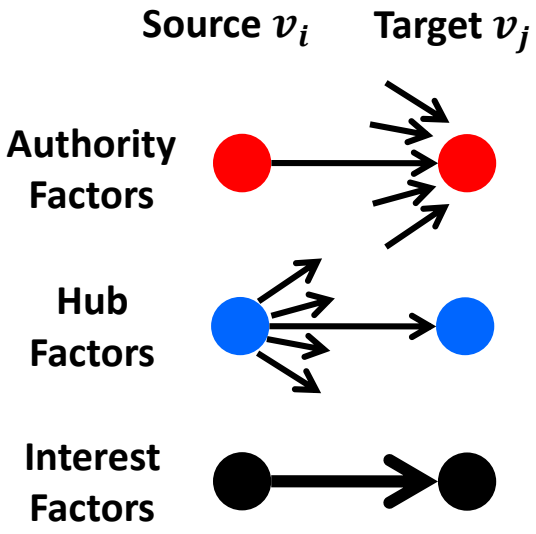
Six Node Factors



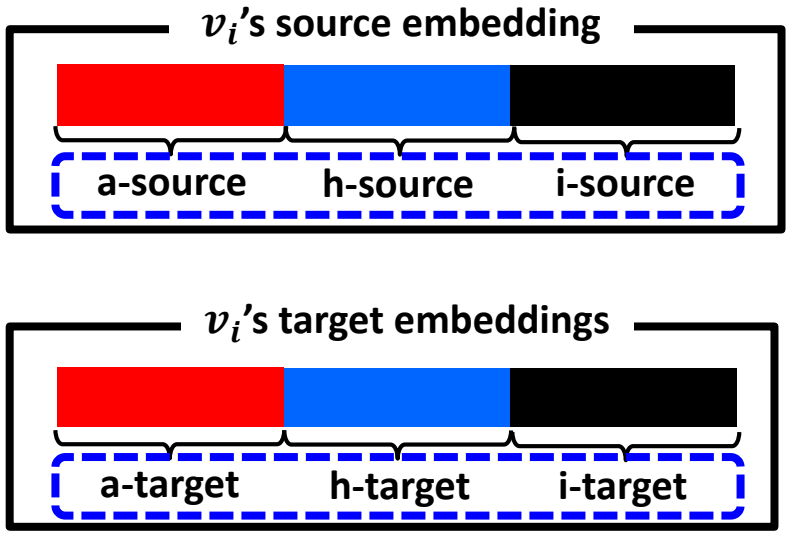
Disentangled Source/Target Embeddings of a node

Overview of ODIN (cont'd)

(STAGE 1) Factor Modeling

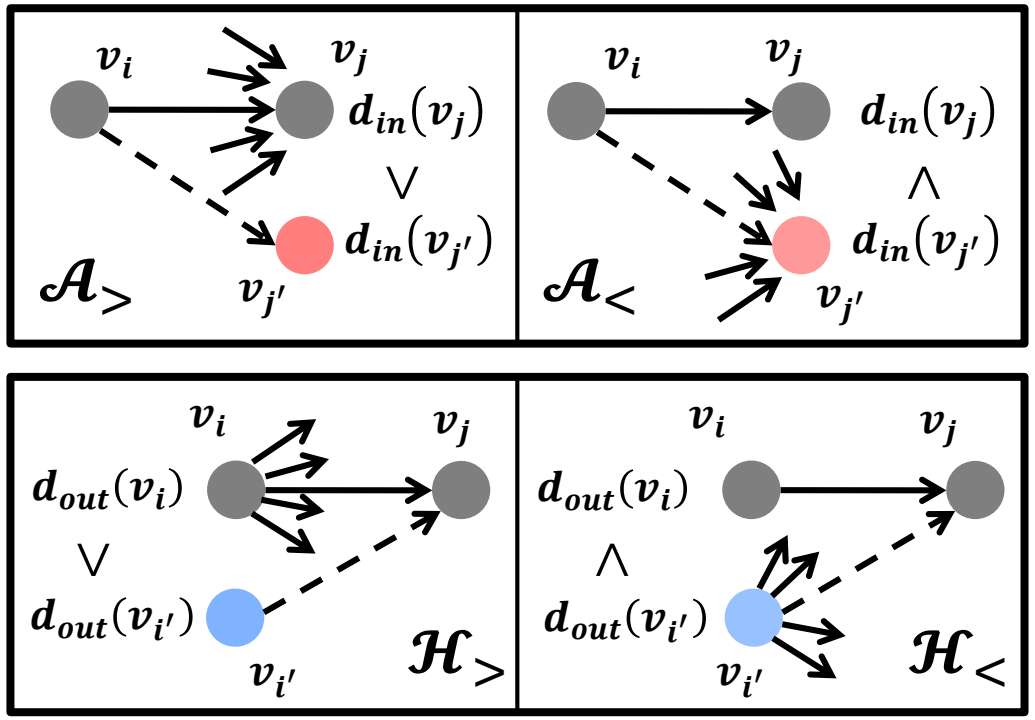


Six Node Factors

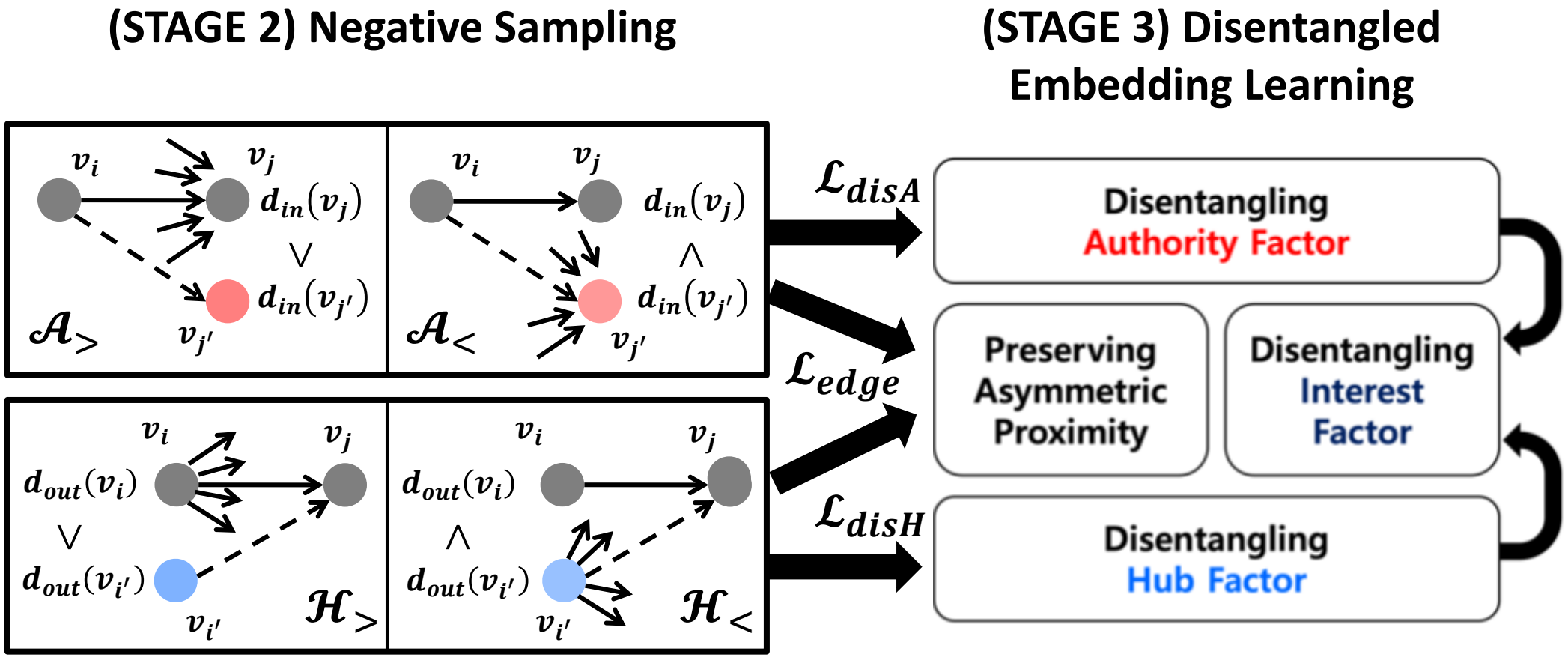


Disentangled Source/Target Embeddings of a node

(STAGE 2) Negative Sampling

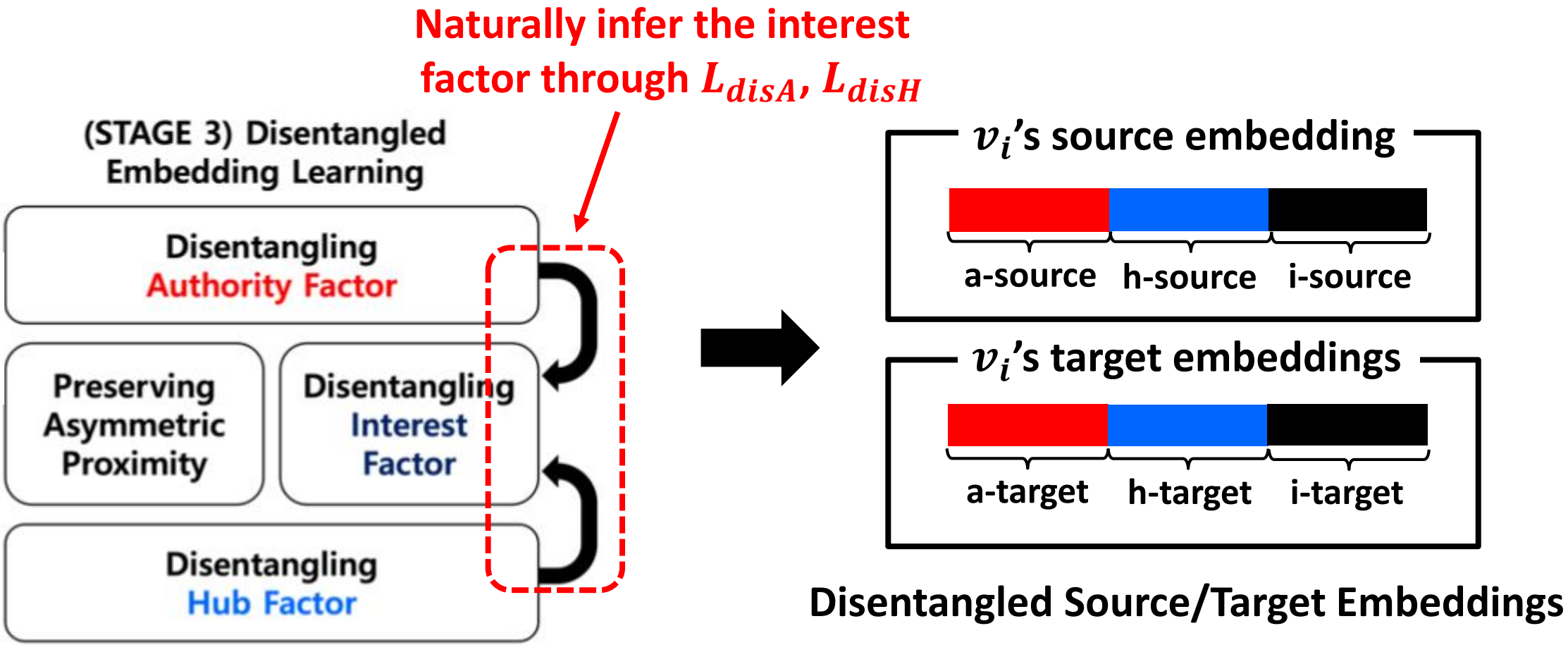


Overview of ODIN (cont'd)



Final Embeddings

- Sub-embeddings capture degree-related biases and interest separately
- Thus, final embeddings are robust to the shifts in degree distributions



Experimental Settings

Datasets

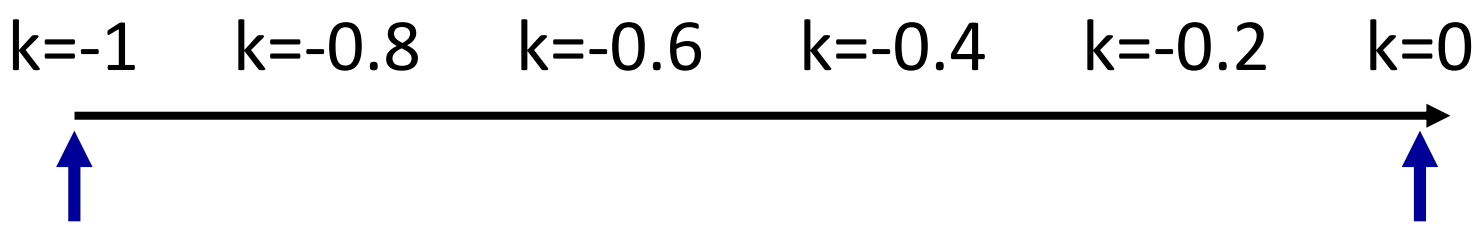
Datasets	GNU	Wiki	JUNG	Ciao
Nodes	6,301	7,115	6,120	4,658
Edges	20,777	103,689	50,535	40,133
Reciprocity	0.00%	5.64%	0.90%	34.90%
Types	P2P	Election	Software	Trust

Nine competitors

- 2 undirected NE methods
  - DeepWalk [KDD'14]
  - Node2Vec [KDD'16]
- 7 directed NE methods
  - APP [AAAI'17]
  - ATP [AAAI'19]
  - NERD [ECML-PKDD'19]
  - GVAE [CIKM'19]
  - DiGCN [NeurIPS'20]
  - MagNet [NeurIPS'21]
  - DGGAN [AAAI'21]

Non-ID Settings

- **Design two types of non-ID settings by splitting the edges in an input network into training and test sets with different degree distributions**
  1. Non-ID (in), where in-degree distributions are different
     - Each edge (v_i, v_j) is sampled into the test set with $p_{ij}^{in} \propto d_{in}(v_j)^k$
  2. Non-ID (out), where out-degree distributions are different
     - Each edge (v_i, v_j) is sampled into the test set with $p_{ij}^{out} \propto d_{out}(v_i)^k$



Shifts are strong
(i.e., sampled inversely proportional to the node degrees)

ID setting
(i.e., sampled randomly)

Results for RQ1

Comparison with nine competitors (when k=-1)

(a) Non-ID (in)

Datasets	Tasks	Undirected NE		Directed NE							ODIN
		DeepWalk	Node2Vec	APP	GVAE	NERD	ATP	DiGCN	MagNet	DGGAN	
GNU	U-LP	0.593±0.005	0.587±0.004	0.675±0.003	0.675±0.003	0.683±0.008	0.731±0.003	0.729±0.001	0.742±0.001	0.722±0.003	**0.760±0.004**
	B-LP	0.648±0.006	0.621±0.010	0.700±0.006	0.748±0.013	0.838±0.004	0.910±0.002	0.878±0.003	0.900±0.004	0.901±0.003	**0.924±0.001**
Wiki	U-LP	0.806±0.001	0.804±0.002	0.795±0.001	0.820±0.005	0.828±0.001	0.827±0.002	0.729±0.002	0.865±0.001	0.890±0.001	**0.905±0.001**
	B-LP	0.852±0.002	0.855±0.007	0.637±0.008	0.901±0.012	0.915±0.002	0.954±0.001	0.862±0.002	0.928±0.001	0.963±0.001	**0.973±0.001**
JUNG	U-LP	0.725±0.005	0.777±0.006	0.741±0.002	0.820±0.003	0.784±0.006	0.864±0.001	0.817±0.004	0.816±0.002	0.879±0.003	**0.884±0.002**
	B-LP	0.810±0.005	0.861±0.005	0.772±0.005	0.902±0.006	0.883±0.005	0.961±0.001	0.926±0.001	0.891±0.003	0.964±0.002	**0.969±0.001**
Ciao	U-LP	0.776±0.004	0.778±0.002	0.846±0.001	0.841±0.002	0.857±0.002	0.846±0.002	0.641±0.004	0.847±0.001	0.886±0.001	**0.892±0.001**
	B-LP	0.688±0.005	0.725±0.006	0.768±0.002	0.797±0.004	0.869±0.006	0.887±0.003	0.751±0.006	0.873±0.004	0.912±0.003	**0.914±0.003**

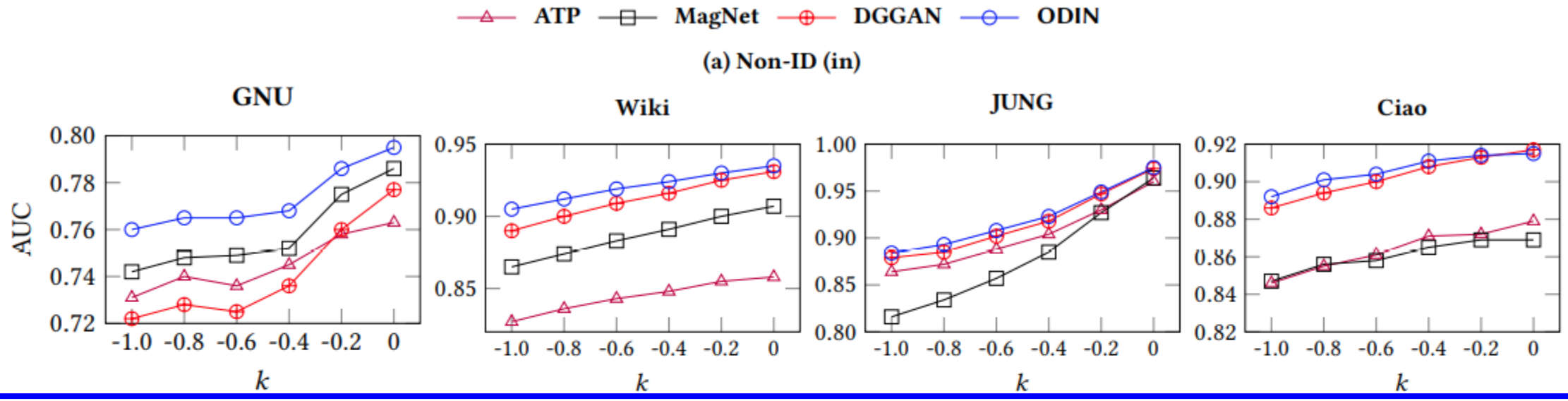
(b) Non-ID (out)

		Undirected NE		Directed NE							
	B-LP	0.635±0.011	0.695±0.004	0.597±0.004	0.684±0.008	0.750±0.004	0.867±0.003	0.836±0.003	0.827±0.003	0.871±0.002	**0.883±0.003**

- Best competitors change depending on tasks, datasets, and non-ID settings
- ODIN is effective compared to all the competitors in addressing the OOD generalization problem against degree-related distributional shifts on directed NE

Results for RQ2

☐ Effect of k on the link prediction performance



- In the ID setting (i.e., $k = 0$), the AUCs of ODIN are comparable to or higher than that of the strongest competitors
- ODIN shows the smallest accuracy degradation and, accordingly, the accuracy gain of ODIN against competitors steadily increases
- The results indicate that ODIN obtains OOD generalized embeddings robust to degree-related distributional shifts

Conclusions

- **(Observation)** We pointed out that the existing directed NE methods face difficulties in effectively addressing the OOD generalization problem
- **(Effective Algorithm)** We proposed ODIN, which models multiple factors in the formation of directed edges and learns disentangled embeddings
- **(Extensive Experiments)** Through extensive experiments, we showed clearly the effectiveness of our strategies for factor modeling and disentangled embedding learning

Source Code: https://github.com/hsyoo32/odin

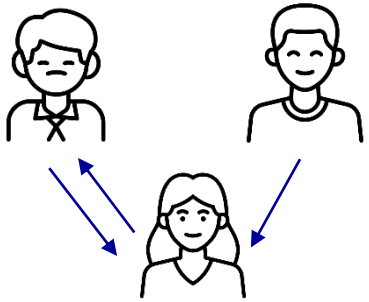
Thank You !

Contact: yeonchang@gatech.edu

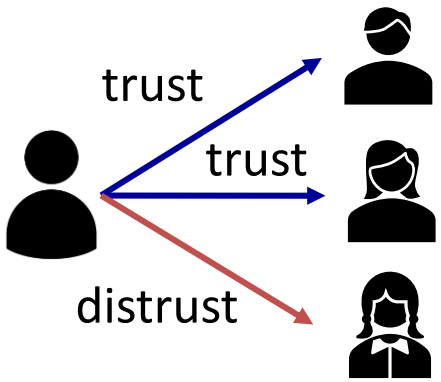
Appendix

Background: Network Embedding (NE) (cont'd)

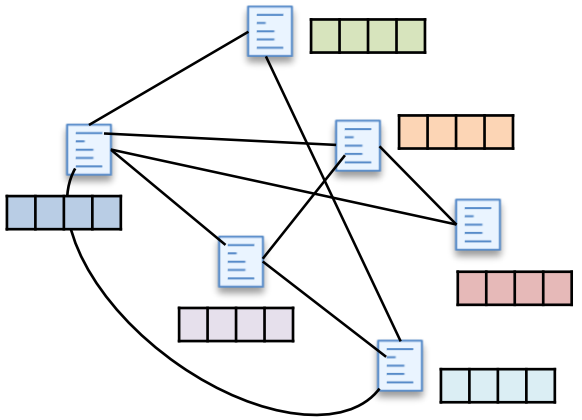
- **In recent studies, additional information has been incorporated to improve the accuracy of NE**
  - Edge directions [Tong et al. NeurIPS'20; Yoo et al. WSDM'22]
    - e.g., follower and followee
  - Edge signs [Lee et al. SIGIR'20; Liu et al. KDD'21]
    - e.g., trust and distrust
  - Node attributes [Gao et al. IJCAI'18; Pan et al. WSDM'21]
    - e.g., bag-of-words



(a) Directed Network



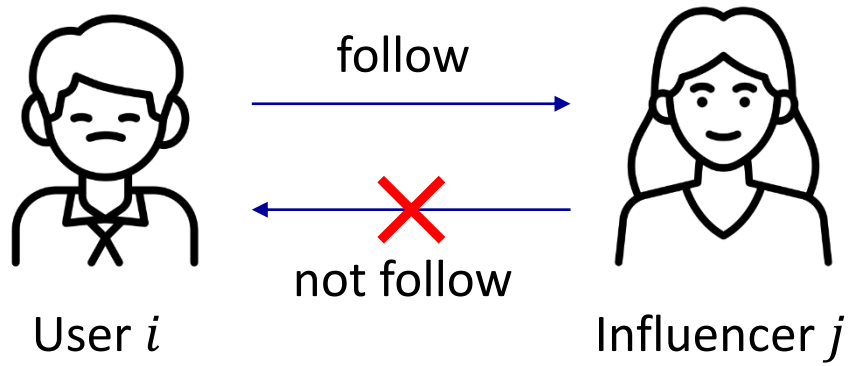
(b) Signed Network



(c) Attributed Network

Background: Directed Network

- **A directed network**
  - A directed edge from node i to j expresses an asymmetric relationship (or proximities) between two nodes
  - A toy example on Instagram



- **To capture such asymmetric relationships accurately, various directed network embedding (DNE) methods have been proposed**
  - APP [AAAI'17]
  - ATP [AAAI'19]
  - NERD [ECML-PKDD'19]
  - GVAE [CIKM'19]
  - DiGCN [NeurIPS'20]
  - MagNet [NeurIPS'21]
  - DGGAN [AAAI'21]

Related Work

	Methods
Matrix Factorization (MF)-based Methods	**HOPE** Asymmetric Transitivity Preserving Graph Embedding [KDD-2016]
	ATP Directed Graph Embedding with Asymmetric Transitivity Preservation [AAAI-2019]
Deep Learning (DL)-based Methods	**GVAE** Gravity-Inspired Graph Autoencoders for Directed Link Prediction [CIKM-2019]
	DiGCN Digraph Inception Convolutional Networks [NeurIPS-2020]
Random Walk (RW)-based Methods	**APP** Scalable Graph Embedding for Asymmetric Proximity [AAAI-2017]
	NERD Node Representation Learning for Directed Grpahs [ECML-PKDD-2019]

MF-based and DL-based Methods

1. **Represent the asymmetric proximities between source and target nodes in the form of a matrix**
   - **ATP** [AAAI'19] uses a measurement that captures both the **hierarchy and reachability between nodes** in the network
   - **GravityAE/VAE** [CIKM'19] and **DiGCN** [NeurIPS'20] use the asymmetric adjacency matrix of the input network

2. **Obtain source and target embeddings of nodes**
   - By using MF techniques (e.g., SVD)
   - By using DL techniques (e.g., autoencoders and GCNs)

RW-based Methods

1. For each seed node,

- Sample a number of positive nodes visited during RWs
  - **APP** [AAAI'17] employs a RW strategy that starts from a seed node and then **follows out-going edges randomly**
  - **NERD** [ECML-PKDD'19] proposes an alternating RW strategy that starts from a seed node and **follows out-going/in-coming edges alternately**
- Sample negative nodes uniformly at random as well

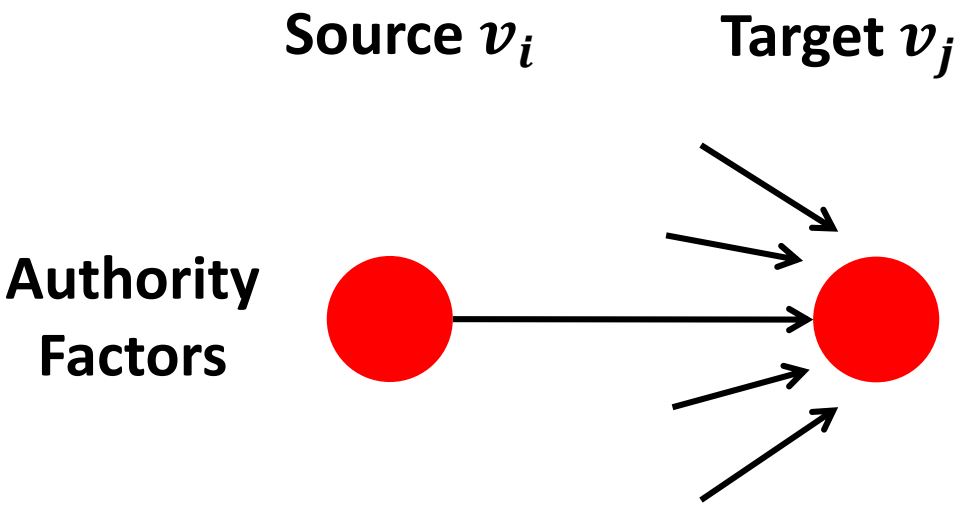
2. Obtain source and target embeddings of nodes

- Maximize the proximities between source embedding of each seed node and target embedding of positive nodes
- Minimize the proximities between source embedding of each seed node and target embedding of negative nodes

(STAGE 1) Factor Modeling

- **Model the formation of each directed edge (v_i, v_j) based on six node factors grouped as follows:**

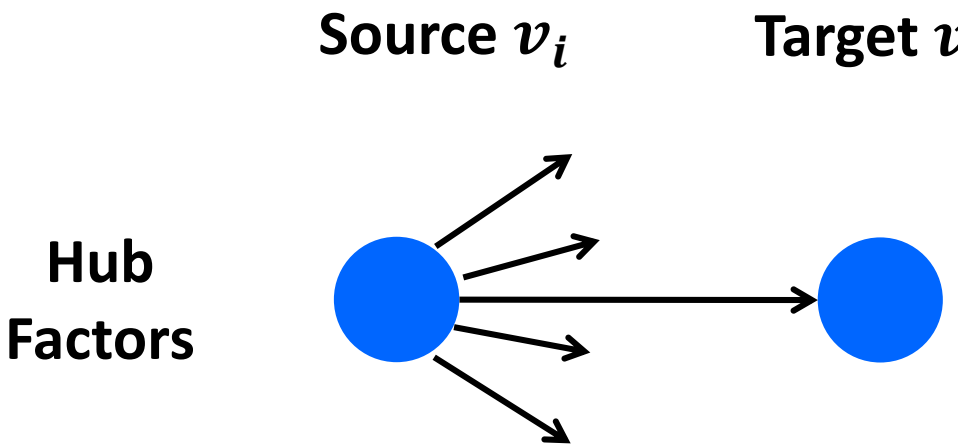
1. **Authority factors**
   - (a) The target v_j's authority status **(a-target)** and (b) the source v_i's bias toward authorities **(a-source)**
   - They together model a bias related to target v_j's authority status (i.e., in-degree)



(STAGE 1) Factor Modeling (cont'd)

- **Model the formation of each directed edge (v_i, v_j) based on six node factors grouped as follows:**

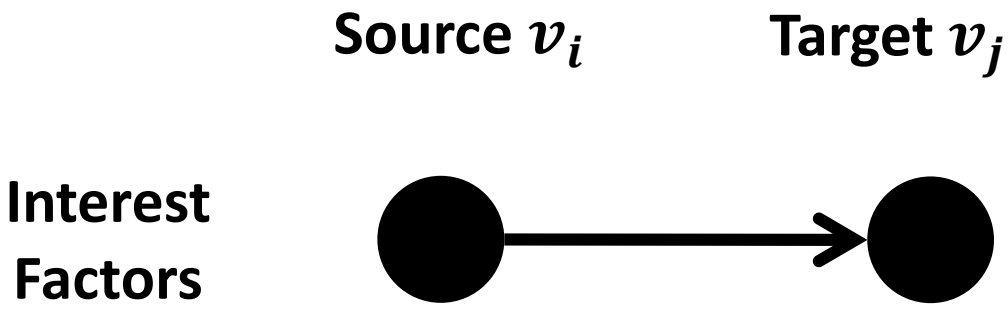
  2. **Hub factors**
     - (a) The source v_i's hub status **(h-source)** and (b) the target v_j's bias toward hubs **(h-target)**
     - They together model a bias related to source v_i's hub status (i.e., out-degree)



(STAGE 1) Factor Modeling (cont'd)

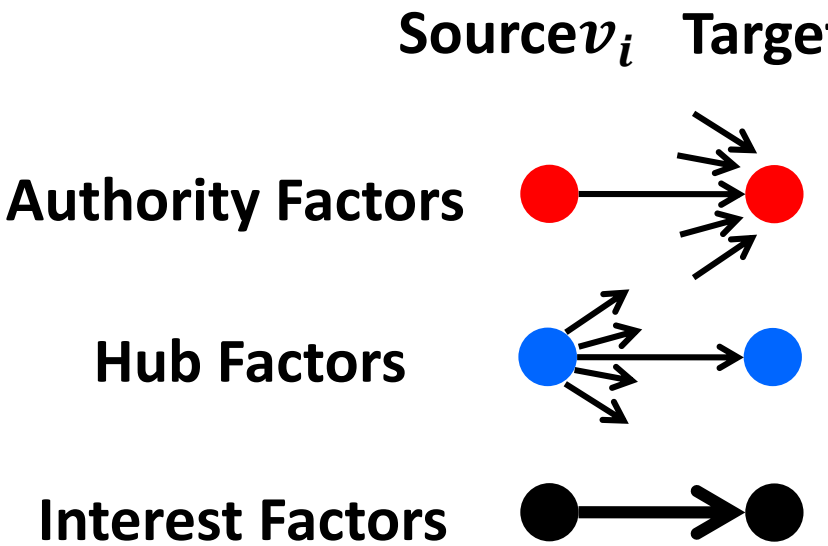
- **Model the formation of each directed edge (v_i, v_j) based on six node factors grouped as follows:**

  3. **Interest factors**
     - (a) The source v_i's intrinsic property as a source **(i-source)** and (b) the target v_j's intrinsic property as a target **(i-target)**
     - They together model the pure interest in forming an edge from v_i to v_j after removing degree-related biases

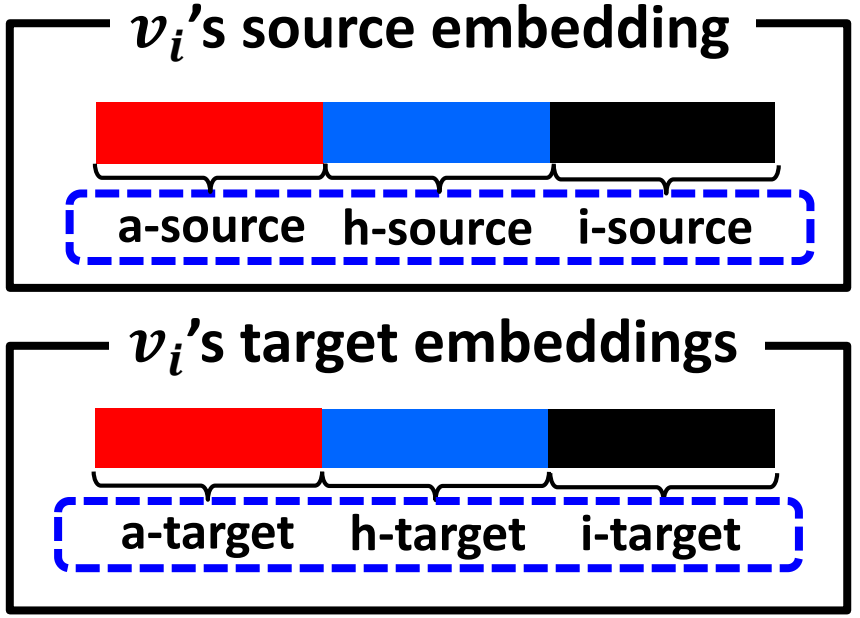


(STAGE 1) Factor Modeling (cont'd)

- Represent a node v_i as six factor sub-embeddings
  - Source role: $\mathbf{a}_i^{src}, \mathbf{h}_i^{src}, \mathbf{i}_i^{src}$
  - Target role: $\mathbf{a}_i^{tar}, \mathbf{h}_i^{tar}, \mathbf{i}_i^{tar}$
- Concatenate the three factor sub-embeddings as a source/target
  - $\mathbf{s}_i = \boldsymbol{a}_i^{src} \oplus \boldsymbol{h}_i^{src} \oplus \boldsymbol{i}_i^{src}$,
  - $\mathbf{t}_i = \boldsymbol{a}_i^{tar} \oplus \boldsymbol{h}_i^{tar} \oplus \boldsymbol{i}_i^{tar}$



Six Node Factors



Disentangled Source/Target Embeddings

(STAGE 1) Factor Modeling (cont'd)

- **Compute three factor scores based on the six factor sub-embeddings**
  - Represent how much (a) the authority factor, (b) the hub factor, and (c) the interest factor affect the formation of the directed edge $(\boldsymbol{v_i}, \boldsymbol{v_j})$

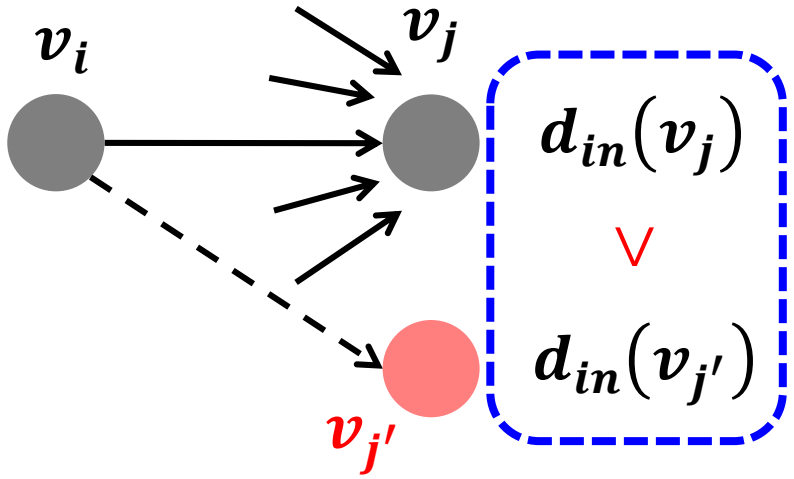
(a) $\boldsymbol{s_{ij}^{auth}} = \mathbf{a}_i^{src} \circ \mathbf{a}_j^{tar}$ (b) $\boldsymbol{s_{ij}^{hub}} = \mathbf{h}_i^{src} \circ \mathbf{h}_j^{tar}$ (c) $\boldsymbol{s_{ij}^{int}} = \mathbf{i}_i^{src} \circ \mathbf{i}_j^{tar}$

- **Compute the overall edge score by adding the three factor scores**
  - Represent the likelihood of the formation of a directed edge $(\boldsymbol{v_i}, \boldsymbol{v_j})$

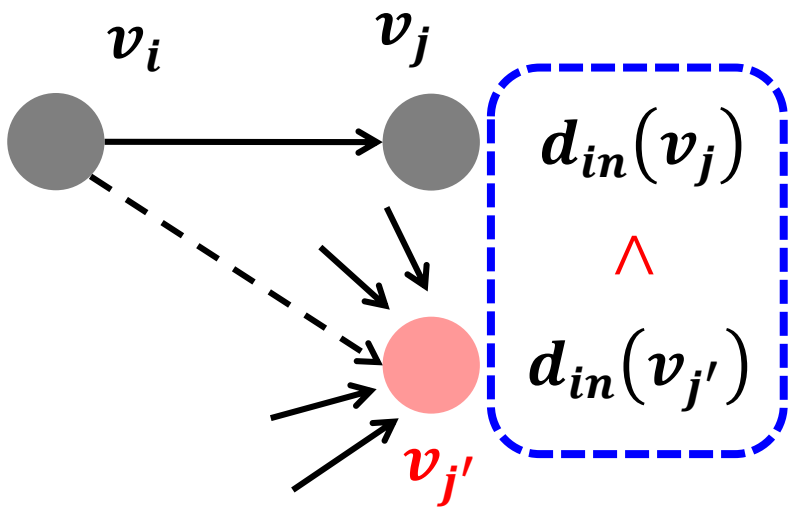
$$\boldsymbol{s_{ij}^{edge}} = \boldsymbol{s_{ij}^{auth}} + \boldsymbol{s_{ij}^{hub}} + \boldsymbol{s_{ij}^{int}} (= \mathbf{s}_i \circ \mathbf{t}_i)$$

(STAGE 2) Negative Sampling

- For each existent edge (v_i, v_j), sample different types of training instances (i.e., triplets) for embedding learning
  - Type 1



  - Type 2

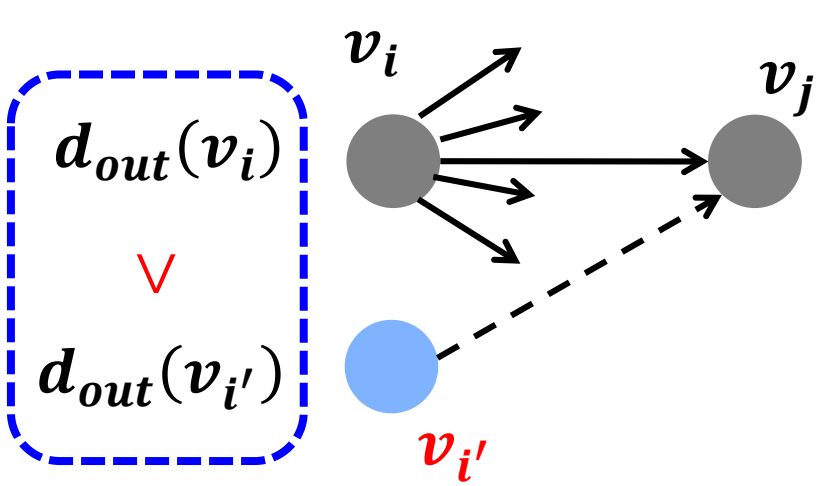


Source: v_i | Positive target: v_j | Negative target: $v_{j'}$

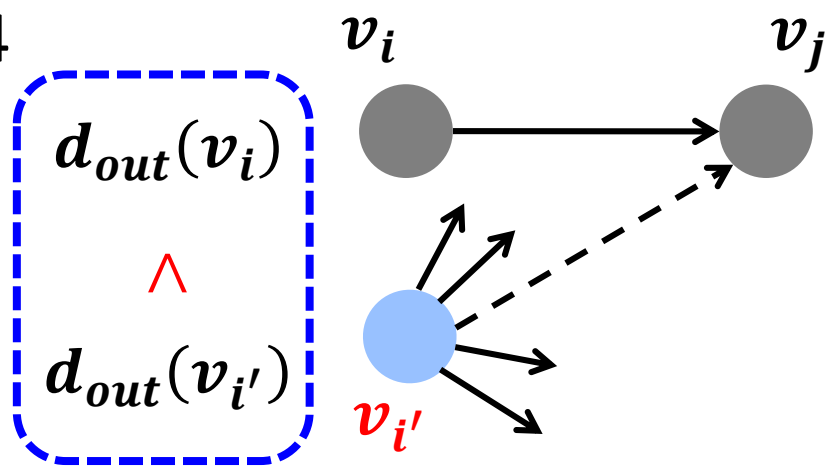
- Add $(v_i, v_j, v_{j'})$ to the sets $A_>$ (for type 1) or $A_<$ (for type 2)
  - Aid in capturing the influence of bias related to the target's in-degree
  - $A = A_> \cup A_<$

(STAGE 2) Negative Sampling (cont'd)

- For each existent edge (v_i, v_j), sample different types of training instances (i.e., triplets) for embedding learning
  - Type 3



  - Type 4

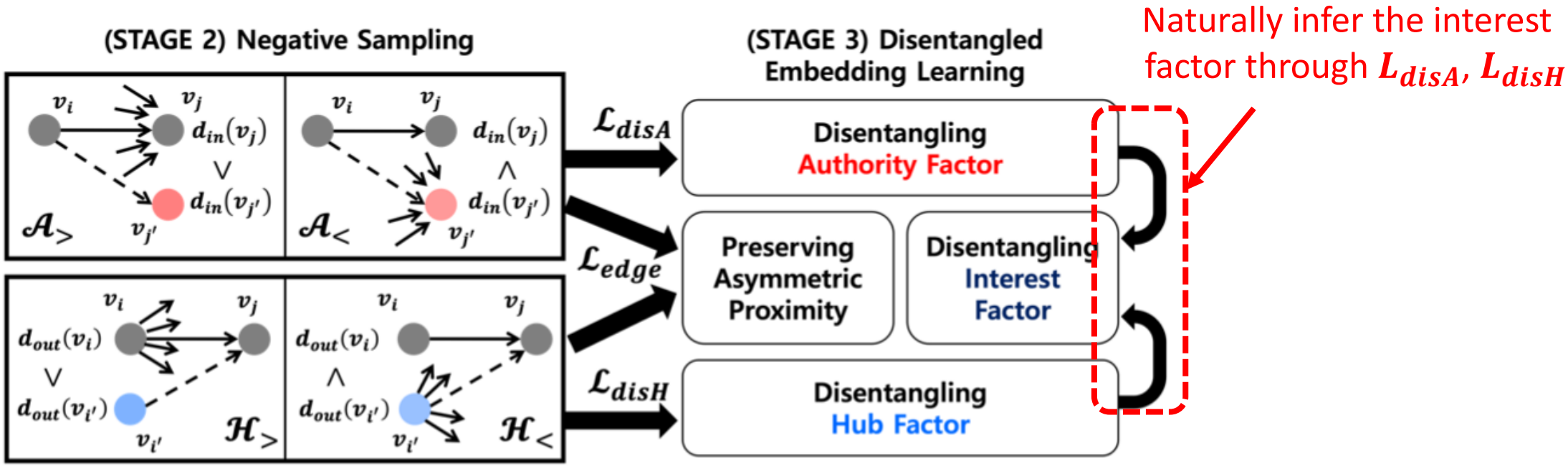


Positive source: v_i Target: v_j Negative source: $v_{i'}$

- Add $(v_i, v_j, v_{i'})$ to the sets $H_>$ (for type 3) or $H_<$ (for type 4)
  - Aid in capturing the influence of bias related to the source's out-degree
  - $H = H_> \cup H_<$

(STAGE 3) Disentangled Embedding Learning

- **Learn the disentangled source and target embeddings of each node based on the sampled instances via the three objectives**
  1. L_{edge}: preserve asymmetric proximity between nodes in input network
  2. L_{disA}: disentangle the authority factor from the other two factors
  3. L_{disH}: disentangle the hub factor from the other two factors



Loss Function: Multi-Objective Learning

$$L = L_{edge}(A \cup H) + \alpha\left(L_{disA}(A) + L_{disH}(H)\right)$$

① **Preserving asymmetric proximities**

② Disentangling the authority factor from the others

③ Disentangling the authority factor from the others

① $L_{edge}(A \cup H) =$

$$*\mathrm{BPR}\left(s_{ij}^{edge}, s_{ij'}^{edge}\right) = -log\left(\sigma\left(s_{ij}^{edge} - s_{ij'}^{edge}\right)\right)$$

$$\sum_{(v_i, v_j, v_{j'}) \in A} \mathrm{BPR}\left(s_{ij}^{edge}, s_{ij'}^{edge}\right) + \sum_{(v_i, v_j, v_{i'}) \in H} \mathrm{BPR}\left(s_{ij}^{edge}, s_{i'j}^{edge}\right)$$

➔ For $(v_i, v_j, v_{j'})$ in A, $s_{ij}^{edge} > s_{ij'}^{edge}$

➔ For $(v_i, v_j, v_{i'})$ in H, $s_{ij}^{edge} > s_{i'j}^{edge}$

However, L_{edge} alone does not contribute to preserving the desired factor in each factor sub-embedding

Loss Function: Multi-Objective Learning (cont'd)

$$L = L_{edge}(A \cup H) + \alpha(L_{disA}(A) + L_{disH}(H))$$

① Preserving asymmetric proximities

② **Disentangling the authority factor from the others**

③ Disentangling the authority factor from the others

② $L_{disA}(A) = L_{auth}(A_{>}) + L_{auth}(A_{<}) + L_{hub+int}(A_{<})$

➔ For $(v_i, v_j, v_{j'})$ in $A_{>}$, $s_{ij}^{auth} > s_{ij'}^{auth}$

- The authority status (i.e., in-degree) of v_j is higher than that of $v_{j'}$
- Thus, if authority-factor scores capture the biases towards authorities, as desired, **$s_{ij}^{auth} > s_{ij'}^{auth}$ should hold!**

Loss Function: Multi-Objective Learning (cont'd)

$$L = L_{edge}(A \cup H) + \alpha(L_{disA}(A) + L_{disH}(H))$$

① Preserving asymmetric proximities

② Disentangling the authority factor from the others

③ **Disentangling the authority factor from the others**

② $L_{disA}(A) = L_{auth}(A_{>}) + L_{auth}(A_{<}) + L_{hub+int}(A_{<})$

➔ For $(v_i, v_j, v_{j'})$ in $A_{<}$, $s_{ij}^{auth} < s_{ij'}^{auth}$

- The authority status (i.e., in-degree) of v_j is lower than that of $v_{j'}$
- Thus, if authority-factor scores capture the biases towards authorities, as desired, **$s_{ij}^{auth} < s_{ij'}^{auth}$ should hold!**

Loss Function: Multi-Objective Learning (cont'd)

$$L = L_{edge}(A \cup H) + \alpha(L_{disA}(A) + L_{disH}(H))$$

① Preserving asymmetric proximities

② **Disentangling the authority factor from the others**

③ Disentangling the authority factor from the others

② $L_{disA}(A) = L_{auth}(A_{>}) + L_{auth}(A_{<}) + L_{hub+int}(A_{<})$

➔ For $(v_i, v_j, v_{j'})$ in $A_{<}$,

$$s_{ij}^{hub} + s_{ij}^{int} > s_{ij'}^{hub} + s_{ij'}^{int}$$

- Even though $s_{ij}^{auth} < s_{ij'}^{auth}$ holds, s_{ij}^{edge} should become higher than $s_{ij'}^{edge}$
- Thus, we can imply the following inequality $s_{ij}^{hub} + s_{ij}^{int} > s_{ij'}^{hub} + s_{ij'}^{int}$!

Loss Function: Multi-Objective Learning (cont'd)

$$L = L_{edge}(A \cup H) + \alpha(L_{disA}(A) + L_{disH}(H))$$

① Preserving asymmetric proximities

② Disentangling the authority factor from the others

③ **Disentangling the authority factor from the others**

$$③\ L_{disH}(H) = L_{hub}(H_{>}) + L_{hub}(H_{<}) + L_{auth+int}(H_{<})$$

For $(v_i, v_j, v_{i'})$ in $H_{>}$,

$$s_{ij}^{hub} > s_{i'j}^{hub}$$

For $(v_i, v_j, v_{i'})$ in $H_{<}$, $s_{ij}^{hub} < s_{i'j}^{hub}$

For $(v_i, v_j, v_{i'})$ in $H_{<}$,

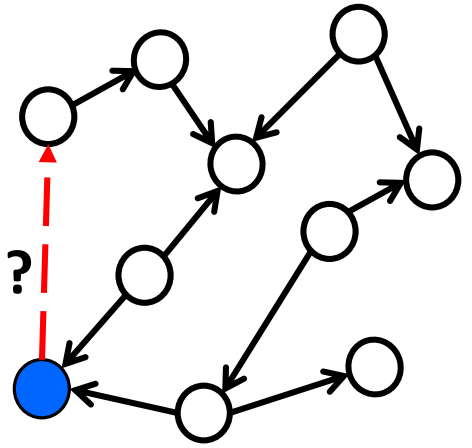
$$s_{ij}^{auth} + s_{ij}^{int} > s_{i'j}^{auth} + s_{i'j}^{int}$$

Why we use all factor-embeddings in OOD link prediction?

- **Learn (bias-aware) hub/authority and (bias-free) interest embeddings**
  - If degree-related biases entirely disappear in test data, it could be beneficial to use interest embeddings only
  - However, in reality, degree-related biases remain but the level of them shifts over time
  - Also, it is not trivial to predict accurately the level of biases in the future
  - Therefore, we leverage all factor-embeddings jointly to achieve high accuracy in any scenario

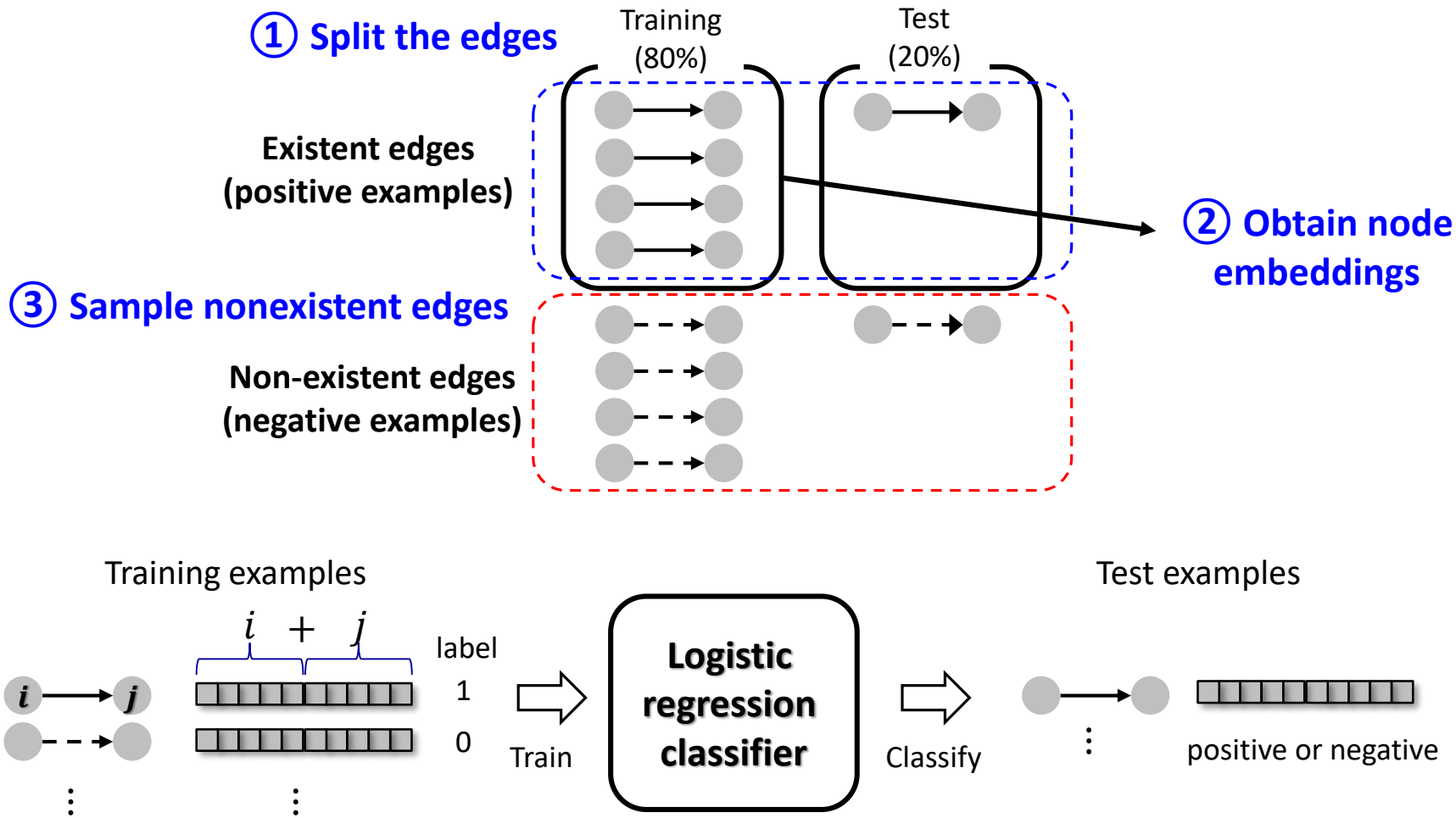
Evaluation Task: Link Prediction (LP)

- **How accurately we can predict the directed edges removed from the input directed network?**



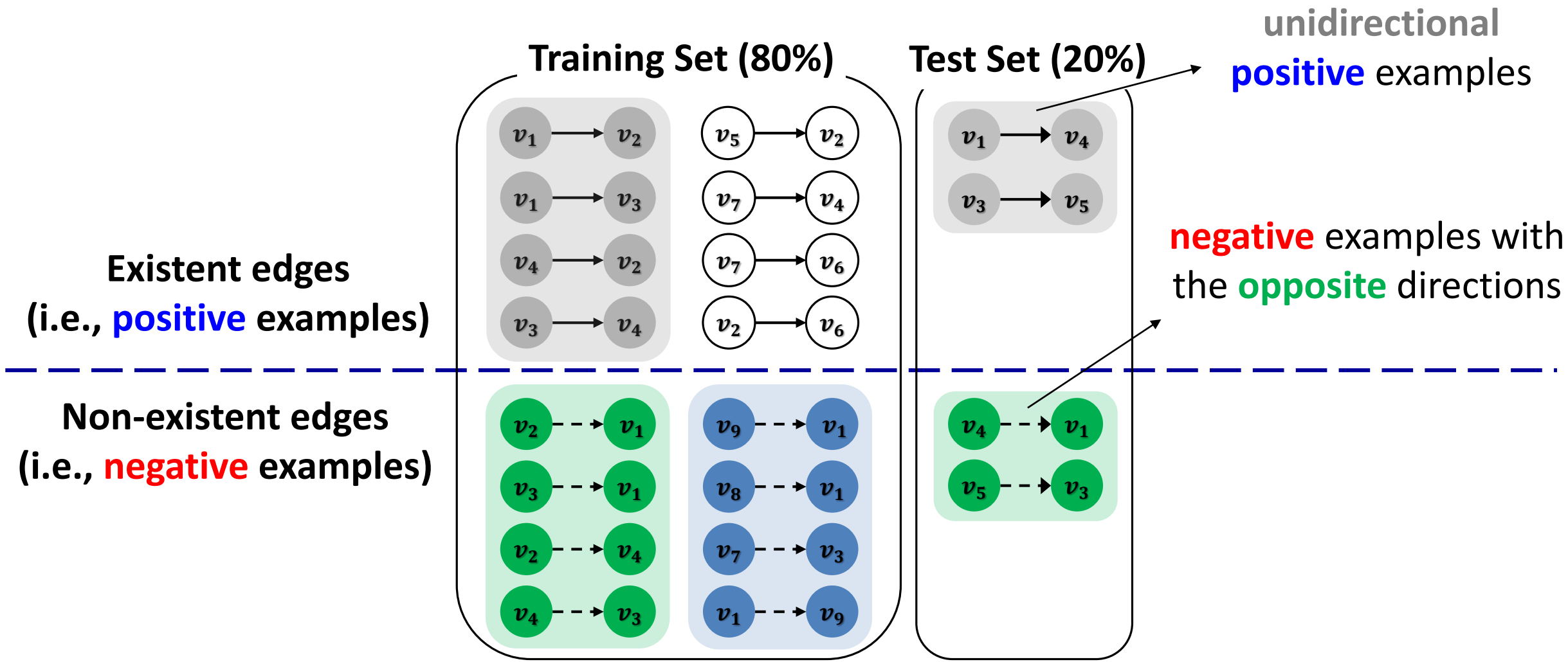
- **Evaluation protocol**
  - Consider the existent edges as positive examples
  - Perform two LP tasks, which depend on how we sample the negative examples
    - **Uniform LP** (U-LP): consider the non-existent edges sampled uniformly at random as negative examples
    - **Biased LP** (B-LP): consider the edges with the opposite directions to (unidirectional) positive examples as negative examples
  - Measure classification accuracy using *area under curve* (AUC)

Evaluation Task



Evaluation Task: Link Prediction (LP)

Example of B-LP



Implementation Details

Competitors

- Dimensionality of embeddings = 120
- Number of walks $\in \{10, 20, 40, 80\}$ (DeepWalk, Node2Vec)
- Walk length $\in \{60, 80, 100\}$ (DeepWalk, Node2Vec)
- $\gamma \in \{5, 10, 15, 20\}$ (NERD)
- $\lambda \in \{0.005, 0.05, 1, 5, 10\}$ (GVAE)
- $\alpha \in \{0.05, 0.1, 0.15, 0.2\}$ (DiGCN)
- $q \in \{0.05, 0.1, 0.15, 0.2, 0.25\}$ (MagNet)

ODIN

- Dimensionality of embeddings = 120 (i.e., dimensionality of each of six factor sub-embeddings = 20)
- $\alpha = 0.5$
- $\beta = 0.01$
- $n = 2$ (i.e., total number of negative samples per edge is 8)

Questions to Be Answered

- **RQ1: Does ODIN outperform its competitors under distributional shifts in degree distributions?**
- **RQ2: How robust is ODIN under various levels of distributional shifts in degree distributions?**
- RO3: Is factor disentanglement effective in ODIN?
- RQ4: How sensitive is ODIN to its hyperparameters?

Note: k is fixed to -1 for RQ1, RQ3, and RQ4 (in $p_{ij}^{in} \propto d_{in}(v_j)^k$ or $p_{ij}^{out} \propto d_{out}(v_i)^k$)

Results for RQ3-1

☐ RQ3-1: Is each of two disentanglement losses effective in ODIN?

■ ODIN_A vs ODIN_{dis_A}

Datasets	Tasks	ODIN_A	ODIN_{disA}
GNU	U-LP	0.632±0.005	**0.763±0.004**
	B-LP	0.704±0.010	**0.927±0.001**
Wiki	U-LP	0.842±0.002	0.896±0.001
	B-LP	0.918±0.001	0.965±0.001
JUNG	U-LP	0.825±0.004	0.878±0.003
	B-LP	0.929±0.003	0.966±0.002
Ciao	U-LP	0.820±0.003	0.890±0.001
	B-LP	0.788±0.009	0.912±0.002

ODIN_A: only uses the *edge loss based on A*

ODIN_{disA}: additionally uses the *disA loss based on A*

■ ODIN_H vs ODIN_{dis_H}

Datasets	Tasks	ODIN_H	ODIN_{disH}
GNU	U-LP	0.604±0.010	0.678±0.001
	B-LP	0.669±0.015	0.820±0.010
Wiki	U-LP	0.793±0.007	0.898±0.001
	B-LP	0.863±0.011	0.968±0.001
JUNG	U-LP	0.714±0.006	**0.884±0.002**
	B-LP	0.830±0.004	**0.970±0.001**
Ciao	U-LP	0.853±0.001	0.886±0.001
	B-LP	0.867±0.005	0.909±0.002

ODIN_H: only uses the *edge loss based on H*

ODIN_{disH}: additionally uses the *disH loss based on H*

■ Each of the disentanglement losses is effective in obtaining embeddings robust to distributional shifts in degree distributions

Results for RQ3-1 (cont'd)

- **RQ3-1: Is each of two disentanglement losses effective in ODIN?**

(a) Non-ID (in)

Datasets	Tasks	ODIN$_A$	ODIN$_{disA}$	ODIN$_H$	ODIN$_{disH}$
GNU	U-LP	0.632±0.005	**0.763±0.004**	0.604±0.010	0.678±0.001
	B-LP	0.704±0.010	**0.927±0.001**	0.669±0.015	0.820±0.010
Wiki	U-LP	0.842±0.002	0.896±0.001	0.793±0.007	0.898±0.001
	B-LP	0.918±0.001	0.965±0.001	0.863±0.011	0.968±0.001
JUNG	U-LP	0.825±0.004	0.878±0.003	0.714±0.006	**0.884±0.002**
	B-LP	0.929±0.003	0.966±0.002	0.830±0.004	**0.970±0.001**
Ciao	U-LP	0.820±0.003	0.890±0.001	0.853±0.001	0.886±0.001
	B-LP	0.788±0.009	0.912±0.002	0.867±0.005	0.909±0.002

(b) Non-ID (out)

Datasets	Tasks	ODIN$_A$	ODIN$_{disA}$	ODIN$_H$	ODIN$_{disH}$
GNU	U-LP	0.648±0.004	**0.786±0.006**	0.668±0.005	0.692±0.007
	B-LP	0.718±0.005	**0.934±0.003**	0.770±0.010	0.835±0.008
Wiki	U-LP	0.853±0.002	0.893±0.001	0.833±0.003	0.895±0.001
	B-LP	0.918±0.001	0.956±0.001	0.894±0.004	0.959±0.001
JUNG	U-LP	0.957±0.003	0.961±0.002	0.890±0.007	**0.963±0.002**
	B-LP	0.993±0.001	**0.995±0.001**	0.969±0.003	**0.995±0.001**
Ciao	U-LP	0.814±0.003	0.877±0.003	0.841±0.002	0.873±0.002
	B-LP	0.764±0.007	0.875±0.002	0.816±0.006	0.867±0.003

Results for RQ3-2

☐ RQ1-2: Is jointly using the both losses effective in ODIN?

(a) Non-ID (in)

Datasets	Tasks	ODIN_{A}	ODIN_{disA}	ODIN_{H}	ODIN_{disH}	ODIN
GNU	U-LP	0.632±0.005	**0.763±0.004**	0.604±0.010	0.678±0.001	0.760±0.004
	B-LP	0.704±0.010	**0.927±0.001**	0.669±0.015	0.820±0.010	0.924±0.001
Wiki	U-LP	0.842±0.002	0.896±0.001	0.793±0.007	0.898±0.001	**0.905±0.001**
	B-LP	0.918±0.001	0.965±0.001	0.863±0.011	0.968±0.001	**0.973±0.001**
JUNG	U-LP	0.825±0.004	0.878±0.003	0.714±0.006	**0.884±0.002**	**0.884±0.002**
	B-LP	0.929±0.003	0.966±0.002	0.830±0.004	**0.970±0.001**	0.969±0.001
Ciao	U-LP	0.820±0.003	0.890±0.001	0.853±0.001	0.886±0.001	**0.892±0.001**
	B-LP	0.788±0.009	0.912±0.002	0.867±0.005	0.909±0.002	**0.914±0.003**

- Superiority between ODIN_{disA} and ODIN_{disH} varies depending on datasets
- ODIN outperforms ODIN_{disA} and ODIN_{disH} in most cases
  - ☐ That is, ODIN can selectively adopt the factor(s) beneficial in each dataset, thereby improving the robustness of embeddings in all datasets

Results for RQ3-2 (cont'd)

RQ1-2: Is jointly using the both losses effective in ODIN?

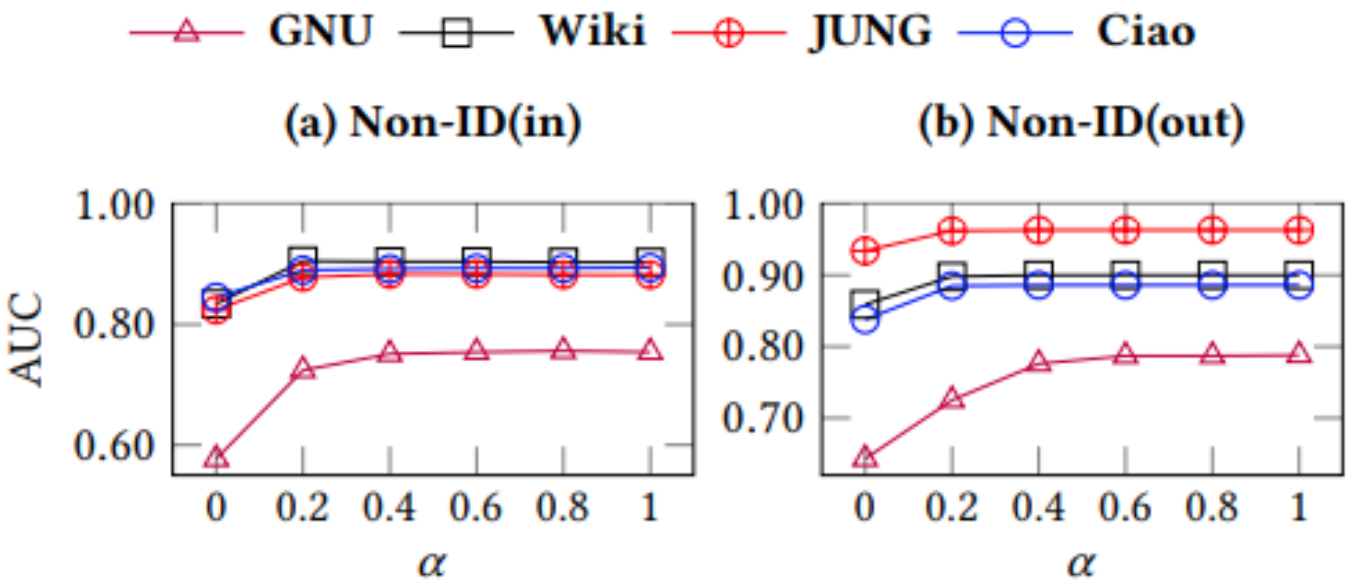
(b) Non-ID (out)

Datasets	Tasks	ODIN_{A}	ODIN_{disA}	ODIN_{H}	ODIN_{disH}	ODIN
GNU	U-LP	0.648±0.004	**0.786±0.006**	0.668±0.005	0.692±0.007	0.782±0.005
	B-LP	0.718±0.005	**0.934±0.003**	0.770±0.010	0.835±0.008	0.927±0.003
Wiki	U-LP	0.853±0.002	0.893±0.001	0.833±0.003	0.895±0.001	**0.900±0.001**
	B-LP	0.918±0.001	0.956±0.001	0.894±0.004	0.959±0.001	**0.962±0.001**
JUNG	U-LP	0.957±0.003	0.961±0.002	0.890±0.007	**0.963±0.002**	0.962±0.002
	B-LP	0.993±0.001	**0.995±0.001**	0.969±0.003	**0.995±0.001**	**0.995±0.001**
Ciao	U-LP	0.814±0.003	0.877±0.003	0.841±0.002	0.873±0.002	**0.883±0.003**
	B-LP	0.764±0.007	0.875±0.002	0.816±0.006	0.867±0.003	**0.883±0.003**

- Superiority between ODIN_{disA} and ODIN_{disH} varies depending on datasets
- ODIN outperforms ODIN_{disA} and ODIN_{disH} in most cases
  - That is, ODIN can selectively adopt the factor(s) beneficial in each dataset, thereby improving the robustness of embeddings in all datasets

Results for RQ4

How the parameter α affects the accuracy of ODIN



$$L = L_{edge}(A \cup B) + \alpha(L_{disA}(A) + L_{disH}(H))$$

- AUCs of ODIN steadily increase until α reaches 0.4 and then the AUCs converge
- ODIN is not highly sensitive to the weight for factor disentanglement