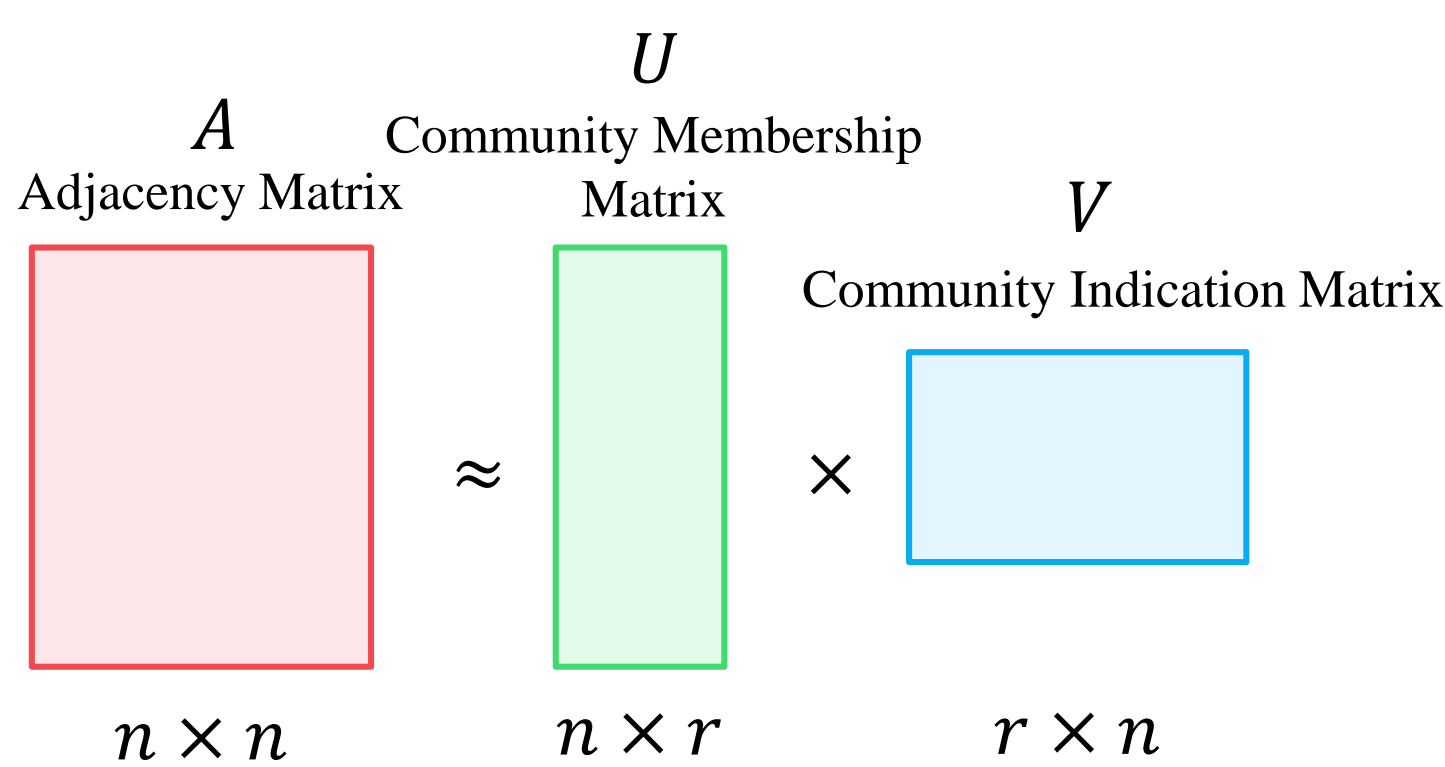
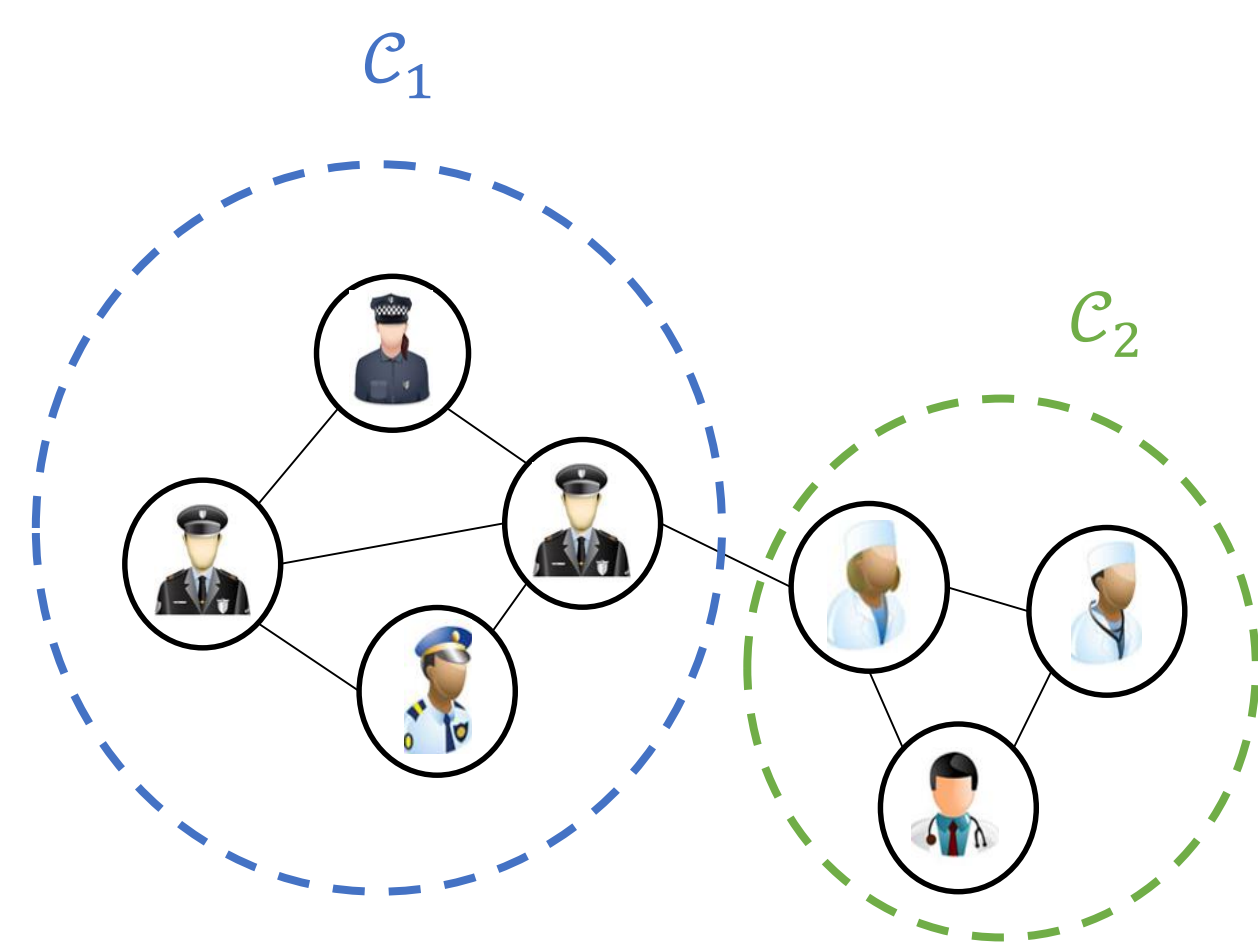


BACKGROUND

Shallow NMF based Network Topology



Community Detection



③ Graph Contrastive Learning Layer

$$\min_{V_p, H_m} L_{cl} = -\frac{1}{n} \sum_{i=1}^n l(V_p(:, i), H_m(:, i))$$

For each node, we have

$$l(V_p(:, i), H_m(:, i)) = \log \frac{e^{\theta(V_p(:, i), H_m(:, i)) / \tau}}{e^{\theta(V_p(:, i), H_m(:, i)) / \tau} + \sum_{k=1}^n \mathbb{1}_{[k \in \tilde{\mathcal{N}}_i]} e^{\theta(V_p(:, i), V_p(:, k)) / \tau}}$$

Consistent with the community semantics implied by graph topology and node attributes, and constructs embedding spaces with significant community structure.

Three shortcomings of existing methods:

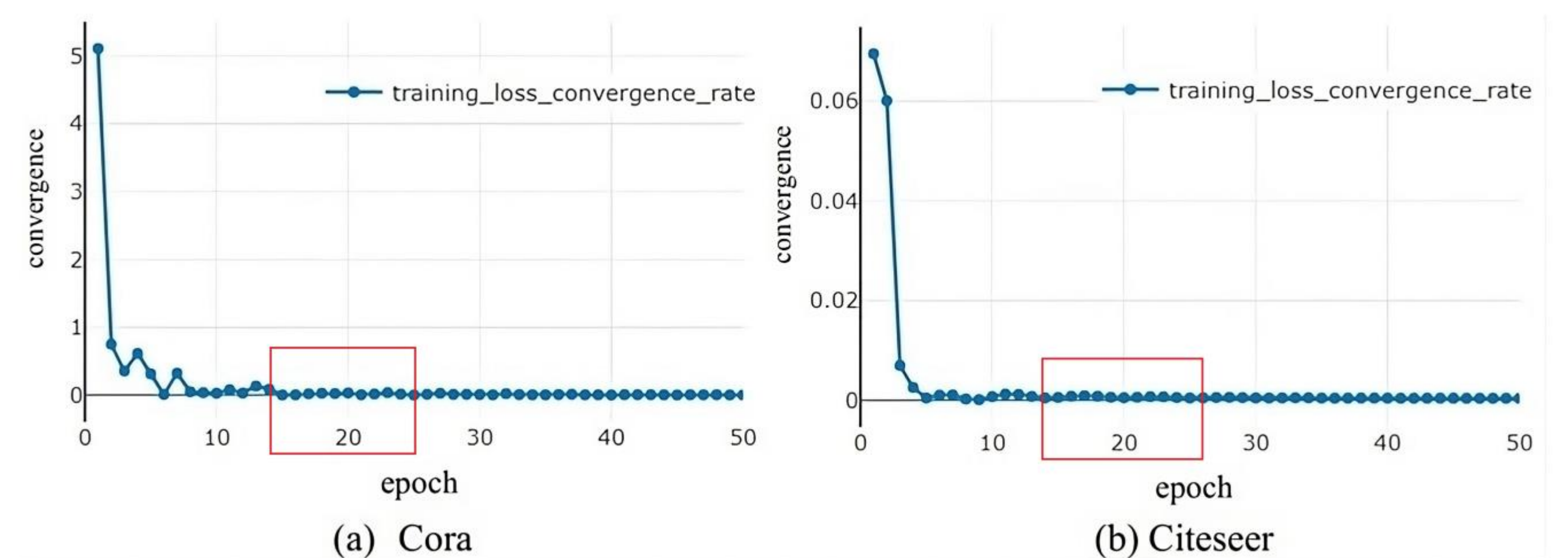
- 1) Directly transform the original network into community membership;
- 2) Only pay attention to the topology of the network and ignore its node attributes;
- 3) Hard to learn the global structure information necessary for community detection.

EXPERIMENTS

① Excellent community detection results

Method	Cora		Citeseer		PubMed	
	ACC	NMI	ACC	NMI	ACC	NMI
NMF	0.4103	0.2851	0.3074	0.1319	0.5133	0.1606
ONMF	0.3811	0.2416	0.3330	0.1423	0.5575	0.1582
BNMF	0.4191	0.2521	0.3324	0.0825	0.5110	0.0714
NSED	0.4234	0.2928	0.3448	0.1492	0.5201	0.1729
LINE	0.4044	0.2376	0.3019	0.0573	0.4990	0.1357
Node2Vec	0.3674	0.1978	0.2521	0.0486	0.4067	0.0635
MNMF	0.1647	0.0035	0.1890	0.0031	0.3397	0.0002
LP-FNMTF	0.2861	0.0261	0.2327	0.0143	0.5437	0.1532
K-means++	0.3230	0.2210	0.4160	0.1910	0.4150	0.2300
VGAER	0.4530	0.2970	0.3020	0.2170	0.3010	0.2230
DNMF	0.4849	0.3572	0.3635	0.1582	0.5389	0.1709
DANMF	0.5499	0.3764	0.4242	0.1831	0.6393	0.2221
Ours	0.6081	0.4006	0.4756	0.2559	0.6653	0.2330

② High running efficiency and fast convergence



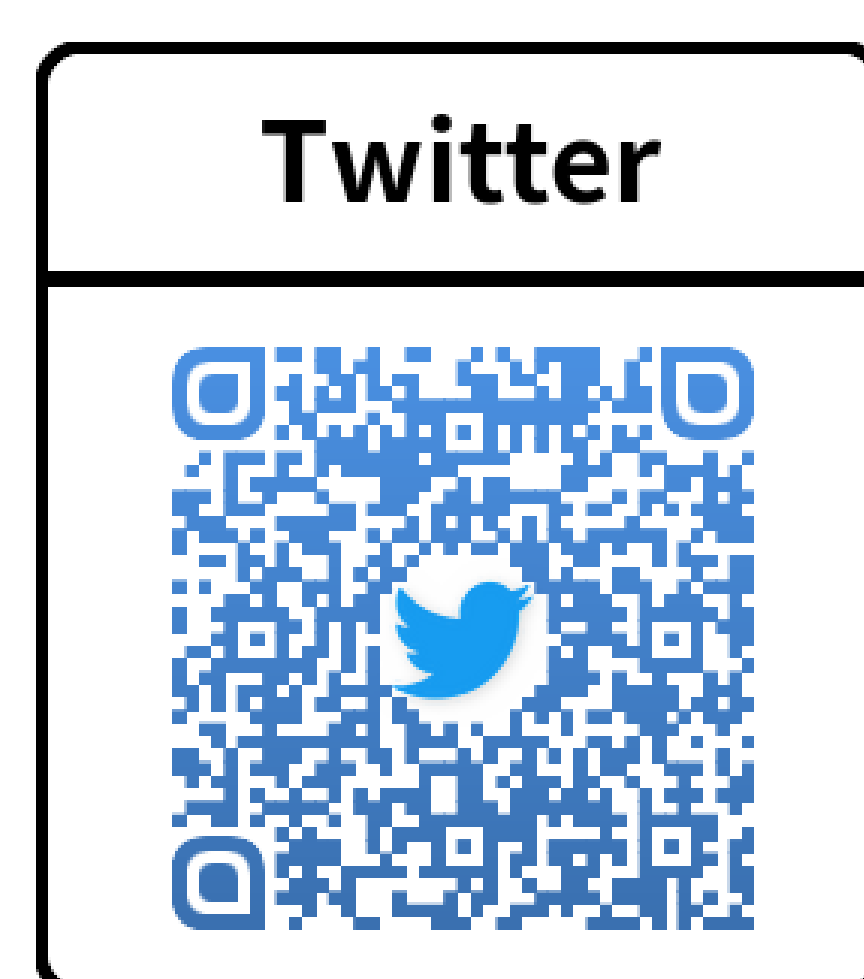
③ Necessity of contrastive schema

Methods	Cora				Citeseer			
	ACC	Δ	NMI	Δ	ACC	Δ	NMI	Δ
Ours [L(A)]	0.5835	2.46%	0.3781	2.25%	0.4598	1.58%	0.1672	8.87%
Ours [L(X)]	0.5162	9.19%	0.3501	5.05%	0.3499	12.6%	0.1749	8.10%
Ours	0.6081		0.4006		0.4756		0.2559	

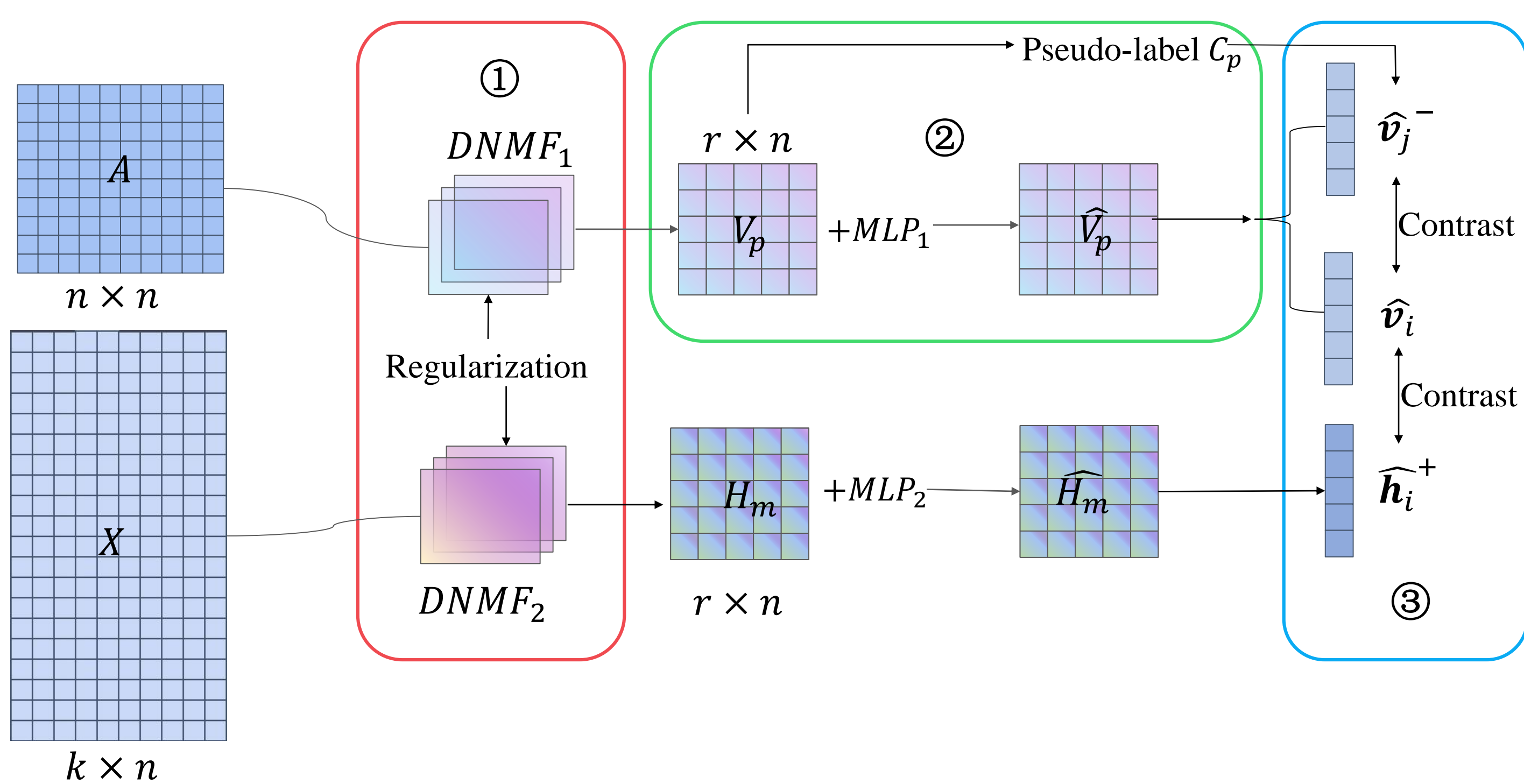
CONCLUSIONS AND FUTURE DIRECTIONS

- We introduce the idea of **contrastive learning** (CL) into the **nonnegative matrix factorization** (NMF) for community detection (CD) **for the first time**, solving the problems of the existing work. The two modules are **mutually reinforcing** and **naturally coupled**.
- Different matrix factorization methods (such as **ONMF**, **BNMF**, **DANMF**, etc.) and other contrastive learning algorithms (such as **MVGRL**, **GRACE**, etc.) could be explored to further derive more community detection algorithms **under the CDNMF framework**.

Paper, Code, Blog and Contact



PROPOSED METHOD: CDNMF



Total objective function of Our **CDNMF**:

$$\min_{U_i, V_p, W_j, H_m} L = L_{DNMF} + \beta L_{reg} + \gamma L_{cl}$$

Key: fusing information about **network topology** (A) and **node attributes** (X) in the framework of NMF using the idea of contrastive learning

① DNMF Layer

$$\min_{U_i, V_p, W_j, H_m} L_{DNMF} = L_A + L_X$$

1.1) Decompose the adjacency matrix A of the graph

$$\min_{U_i, V_p} L_A = \|A - U_1 U_2 \dots U_p V_p\|_F^2 + \alpha \left(\sum_{i=1}^p \|f(U_i)\|_F^2 + \|f(V_p)\|_F^2 \right)$$

1.1.1) Reconstruction loss

$$\min_{U_i, V_p} L_D = \|A - U_1 U_2 \dots U_p V_p\|_F^2$$

s.t. $V_p \geq 0, U_i \geq 0, \forall i = 1, 2, \dots, p$

1.1.2) Nonnegative penalty loss

$$f(B) = \begin{cases} B_{ij}, & B_{ij} < 0 \\ 0, & B_{ij} \geq 0 \end{cases}$$

1.2) Similarly decompose the attribute matrix X of the graph

$$\min_{W_j, H_m} L_X = \|X - W_1 W_2 \dots W_m H_m\|_F^2 + \alpha \left(\sum_{j=1}^m \|f(W_j)\|_F^2 + \|f(H_m)\|_F^2 \right)$$

② Debiased Negative Sampling Layer

$$c_i^* = \operatorname{argmax}(V_p(:, i)) \quad \tilde{\mathcal{N}}_i = \{v_m\} (c_m^* \neq c_i^*)$$

Constructing **community-level discrimination** based on the interpretable results V_p from DNMF.