Deep Contrastive Multiview Network Embedding

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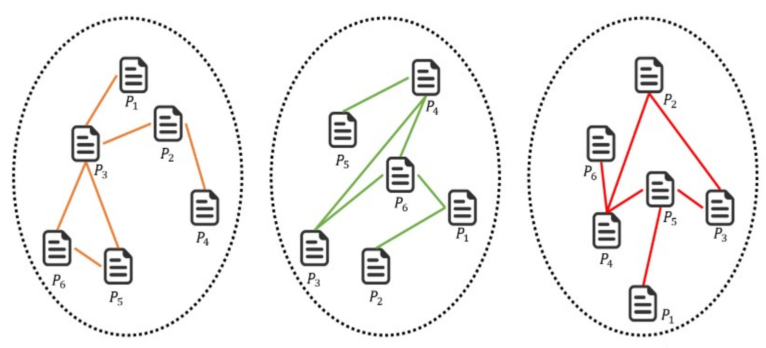
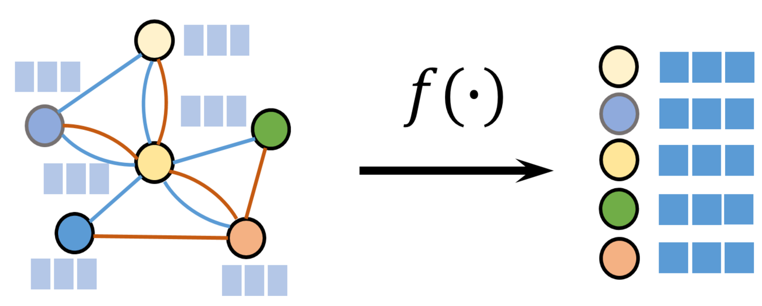
Background

❖ Multiview Networks



❖ Multiview Network Embedding



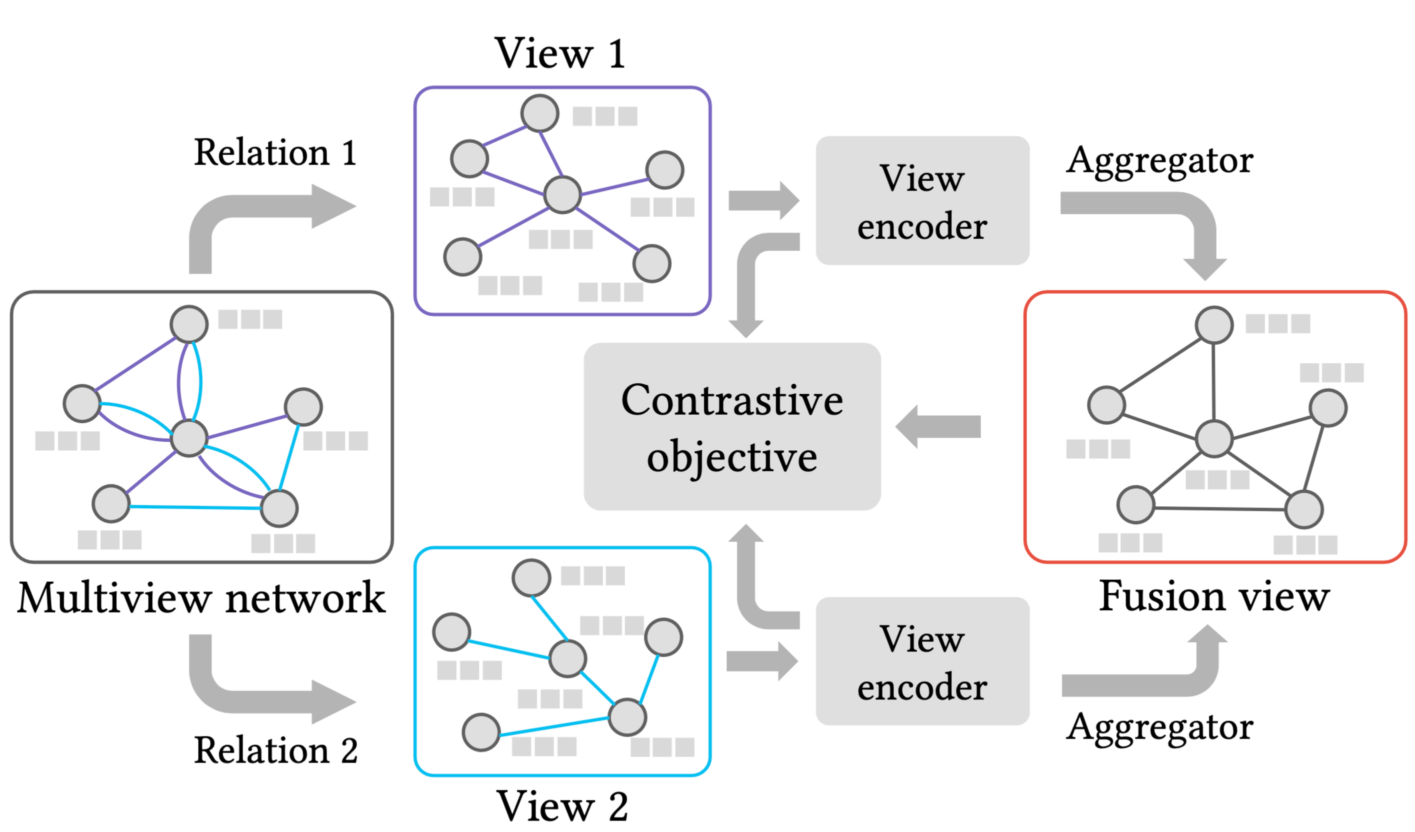
Motivation

❖ Contrastive learning (CL) shows promising performance in multiview network embedding.

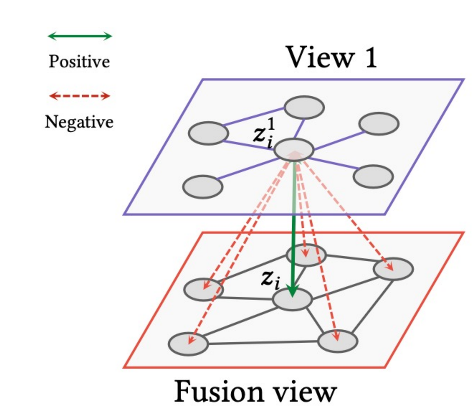
❖ Existing CL methods neglect the semantic consistency between views in the original network.

❖ Furthermore, existing CL methods fail to consider inter-view dependency, leading to suboptimal performance.

The Proposed Method



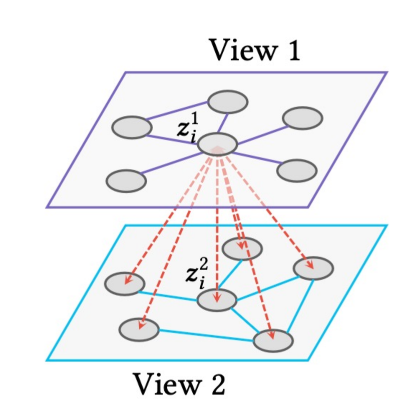
➢ View fusion InfoMax



$$\mathcal{L}_o(z_i^r, z_i) = \log \frac{e^{\theta(z_i^r, z_i)/\tau}}{e^{\theta(z_i^r, z_i)/\tau} + \sum_{j \neq i} e^{\theta(z_i^r, z_j)/\tau} + \sum_{j \neq i} e^{\theta(z_i^r, z_j^r)/\tau}}$$

$$\rho(z_i^r, z_i) = e^{\theta(z_i^r, z_i)/\tau} + \sum_{j \neq i} e^{\theta(z_i^r, z_j)/\tau} + \sum_{j \neq i} e^{\theta(z_i^r, z_j^r)/\tau}$$

➢ Inter-view InfoMin



$$\mathcal{L}(z_i^r, z_i) = \log \frac{e^{\theta(z_i^r, z_i)/\tau}}{\rho(z_i^r, z_i) + \sum_{j \in \mathcal{G}_k} \mathbb{1}_{[k \neq r]} e^{\theta(z_i^r, z_j^k)/\tau}}.$$

Related Work

❖ Relation reconstruction

- ➢ MVE (Tang et al. 2017), MNE (Zhang et al. 2018)
- ➢ CMNA (Chu et al. 2019), GATNE (Cen et al. 2019)

❖ Contrastive learning

- ➢ DMGI (Park et al. 2020)
- ➢ HDMI (Jing et al. 2021)

Experiments

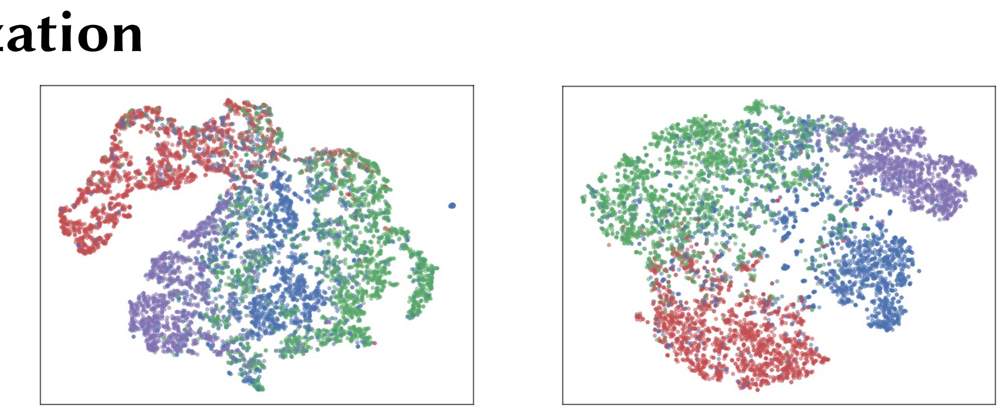
❖Overall Performance

Method	ACM			IMDB			DBLP		
	MaF1	MiF1	NMI	MaF1	MiF1	NMI	MaF1	MiF1	NMI
Deepwalk	0.739	0.748	0.310	0.532	0.55	0.117	0.533	0.537	0.348
node2vec	0.741	0.749	0.309	0.533	0.55	0.123	0.543	0.547	0.382
ANRL	0.819	0.820	0.515	0.573	0.576	0.163	0.770	0.699	0.332
GCN/GAT	0.869	0.870	0.671	0.603	0.611	0.176	0.734	0.717	0.465
DGI	0.881	0.881	0.640	0.598	0.606	0.182	0.723	0.720	0.551
GraphCL	0.892	0.894	0.656	0.613	0.624	0.183	0.736	0.722	0.562
Metapath2vec	0.752	0.758	0.314	0.546	0.574	0.144	0.653	0.649	0.382
HAN	0.878	0.879	0.658	0.599	0.607	0.164	0.716	0.708	0.472
MNE	0.792	0.797	0.545	0.552	0574	0.013	0.566	0.562	0.136
GATNE	0.846	0.841	0.521	0.494	0.504	0.048	0.673	0.665	0.436
DMGI	0.898	<u>0.898</u>	0.687	<u>0.648</u>	<u>0.648</u>	0.196	0.771	0.766	0.409
DMGI-attn	0.887	0.887	<u>0.702</u>	0.602	0.606	0.185	0.778	<u>0.770</u>	<u>0.554</u>
HDMI	<u>0.895</u>	0.894	0.657	0.601	0.610	<u>0.197</u>	<u>0.805</u>	<u>0.795</u>	0.544
CREME	**0.907**	**0.906**	**0.726**	**0.672**	**0.675**	**0.211**	**0.812**	**0.798**	**0.623**

❖Ablation Studies

Variant	ACM			IMDB			DBLP		
	MaF1	MiF1	NMI	MaF1	MiF1	NMI	MaF1	MiF1	NMI
CRE_V-mean	0.786	0.778	0.394	0.519	0.546	0.056	0.801	0.795	0.516
CRE_V-max	0.824	0.828	0.529	0.551	0.562	0.015	0.810	0.796	0.516
CRE_M-mean	0.896	0.896	0.714	0.672	0.673	0.196	0.803	0.783	0.623
CRE_M-max	0.905	0.899	0.723	0.671	0.674	0.203	0.792	0.780	0.606
CRE_C-ori	0.894	0.893	0.725	0.657	0.661	**0.216**	0.795	0.775	0.519
CREME	**0.907**	**0.906**	**0.726**	**0.672**	**0.675**	0.211	**0.812**	**0.798**	**0.623**

❖Visualization



(a) HDMI (b) CREME

Conclusion

❖ We have proposed a novel contrastive framework CREME for multiview network embedding

❖ Our proposed framework contains two collaborative contrastive objectives, view fusion InfoMax and inter-view InfoMin.

❖ Extensive experiments on three real-world multiview networks verify the of CREME.