Semi-Supervised Deep Learning for Multiplex Networks

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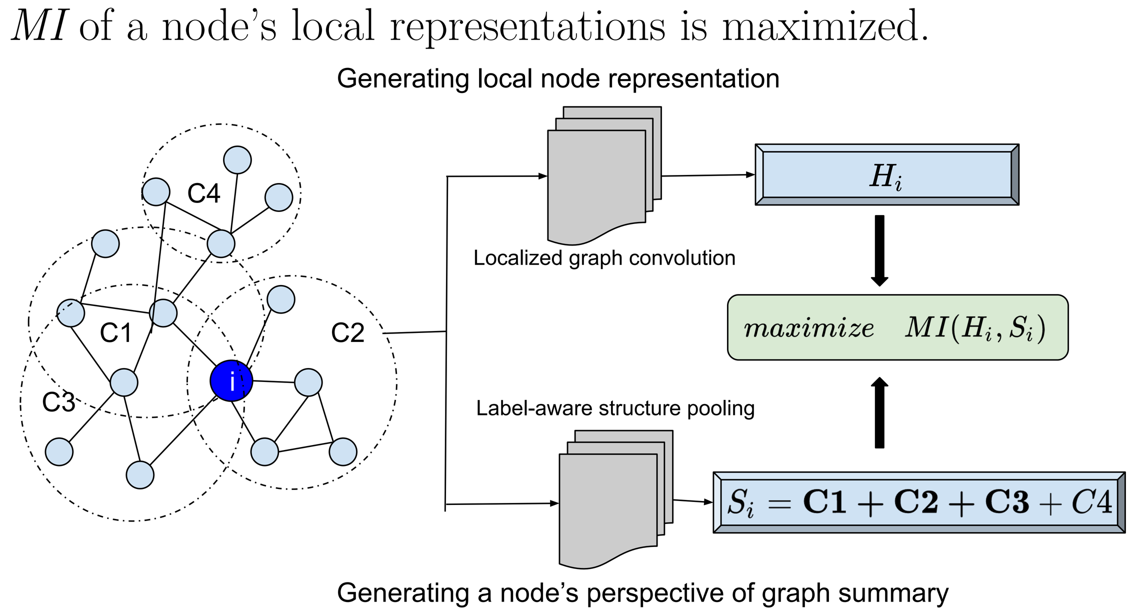
Contribution

A novel structure-aware *InfoMax* based representation learning framework on multiplex networks that use node-contextualized global graph summary for effective joint modeling of nodes and clusters across the layers of a multiplex network.

Key Intuition

In a typical InfoMax based NRL setup, methods naively maximize the *MI* of a node's local representations with a shared identical global context from the underlying graph — encoding trivial and noisy information found across all the nodes' local information. Considering each node is structurally connected differently within the graph, we propose a cluster-based InfoMax objective to learn node representations. The clusters encode the node-specific global graph context, with which the *MI* of a node's local representations is maximized.



Label correlated structure-aware InfoMax

Learning

Ⓐ Given the learned relation-wise clustering information (C_r, H_r) and local node representations, U_r, the contextual global node representation for a node i is computed as a linear combination of different cluster embeddings, C_r^k weighted by its cluster association scores $H_r^i[k], \forall k \in [1, K]$ as,

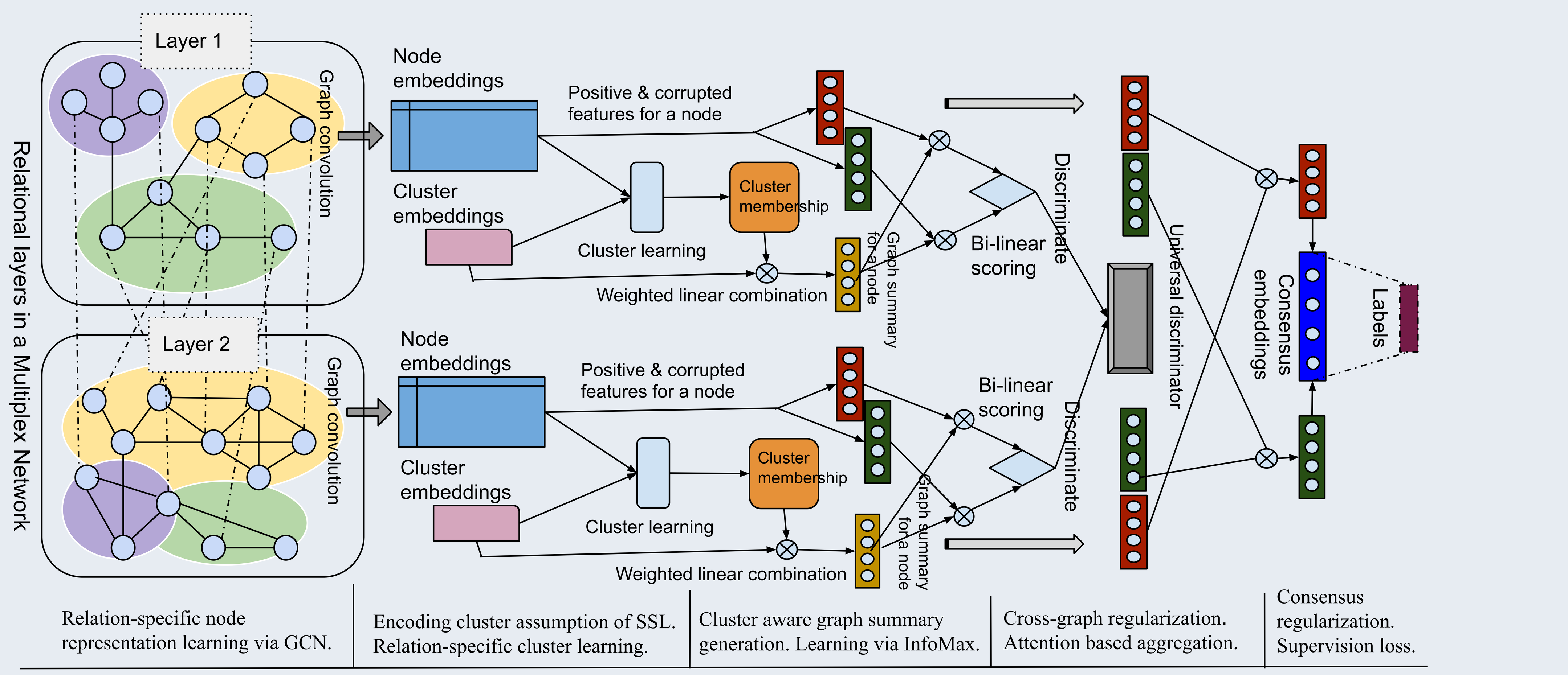
$$S_r^i = \sum_{k=1}^{K} H_r^i[k] C_r^k$$

Ⓑ The node representations are made aware of node-contextualized global graph summary representations, S_r.

$$\mathfrak{O}_{MI} = \sum_{r \in \mathcal{R}} \sum_{i \in \mathcal{V}} \Big(\log(\mathfrak{D}(U_r^i, S_r^i)) + \sum_{j=1}^{N} \log(1 - \mathfrak{D}(\tilde{U}_r^j, S_r^i)) \Big)$$

where $\mathfrak{D} : \mathbb{R}^{2d} \mapsto \mathbb{R}$ is a universal discriminator function that assigns a probability score to a pair of local-global node representations using a bi-linear scoring matrix $B \in \mathbb{R}^{d \times d}$, i.e., $\mathfrak{D}(U_r^i, S_r^i) = \sigma(U_r^{iT} B S_r^i)$, σ being the sigmoid non-linearity.

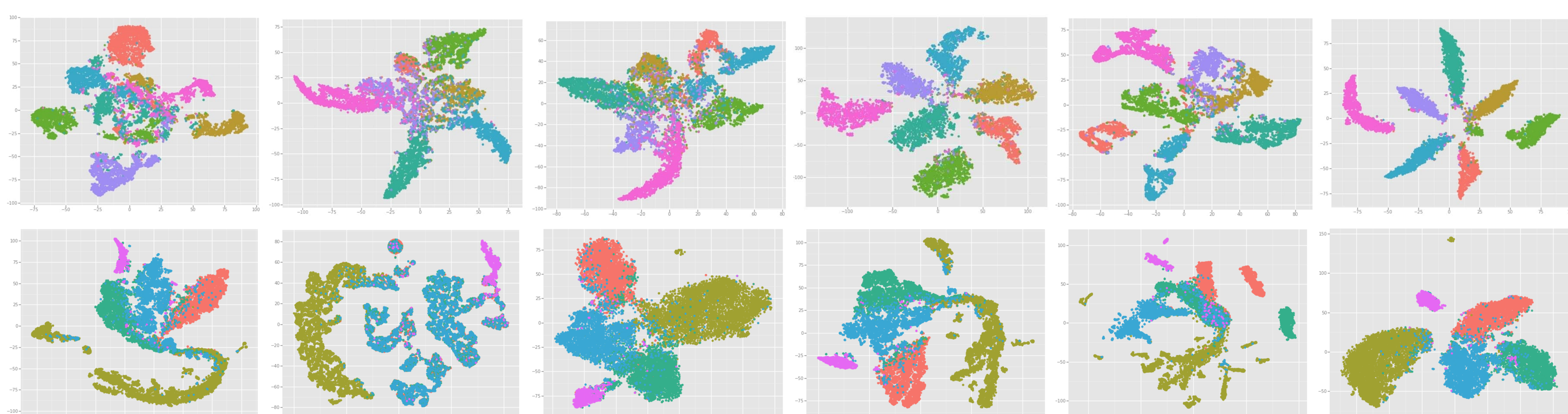
Architecture



Semi-Supervised Deep Clustered Multiplex (SSDCM) with cluster-aware graph summary generation

Explanation of used color-codes. Green: Positive node embeddings, Red: Corrupted node embeddings, Blue: Final consensus embeddings. Orange: Learned cluster membership, Purple: Label information. The color-coded grouping of nodes in relational layers of the example multiplex network denotes different clusters.

Embedding Visualizations



(a) RGCN (b) GUNets (c) MGCN (d) HAN (e) DMGI (f) SSDCM

t-SNE Visualization of node embeddings on FLICKR (top), AMAZON (bottom) for all the SSL methods

BASELINES

	Methods	Tick-mark based comparison.						
		DMGC	DMGI	HAN	MGCN	RGCN	GUNets	SSDCM
Properties	attributes		✓	✓	✓		✓	✓
	within-network	✓	✓	✓	✓	✓	✓	✓
	cross-network	✓		–	✓	–	–	✓
	labels		✓	✓	✓	✓	✓	✓
	global structure	✓	✓				✓	✓
	aggregation		✓	✓		✓		✓

* Dash marks denote Not Applicable (NA).

DATASETS

Dataset	Layers	Nodes	Edges(Total)	Features	Labels
ACM	5	7427	24536689	767	5
DBLP	4	4057	17976710	8920	4
SLAP	6	20419	8207130	2695	15
IMDB-MC	2	3550	80216	2000	3
IMDB-ML	3	18352	2505797	1000	9
FLICKR	2	10364	506051	–	7
AMAZON	3	17857	2194389	2395	5

Results

Micro-F1	ACM	DBLP	SLAP	FLICKR	AMAZON	IMDB-MC	IMDB-ML
DMGC	42.822	84.684	29.819	50.308	69.716	56.278	44.765
RGCN	39.118	83.514	26.914	82.69	72.957	62.542	49.802
GUNets	46.428	87.124	32.985	87.607	77.177	52.508	43.988
MGCN	52.458	87.003	29.563	91.307	84.083	63.384	48.059
HAN	77.441	85.989	30.976	89.478	83.77	62.353	47.117
DMGI	81.205	89.43	30.03	91.225	89.422	65.21	53.413
SSDCM	**88.324**	**94.988**	**33.597**	**96.261**	**92.195**	**67.796**	**54.055**

Table: Node classification results: Micro-F1 scores (%)

NMI-N	ACM	DBLP	SLAP	FLICKR	AMAZON	IMDB-MC	IMDB-ML
DMGC	0.421	0.532	0.245	0.488	0.468	0.185	0.076
RGCN	0.324	0.559	0.24	0.715	0.405	0.193	**0.102**
GUNets	0.65	0.742	0.251	0.758	0.519	0.108	0.036
MGCN	0.41	0.738	0.278	0.76	0.528	0.195	0.033
HAN	0.939	0.66	0.278	0.639	0.519	0.178	0.055
DMGI	0.837	0.682	0.275	0.644	0.568	0.194	0.056
SSDCM	**0.947**	**0.819**	**0.284**	**0.822**	**0.635**	**0.223**	0.085

Table: Node clustering results: NMI scores

Micro-F1 Scores	IMDB_MC	ACM	DBLP	AMAZON	FLICKR
SSDCM [global pool]	65.942	84.176	91.592	90.62	92.698
SSDCM [top-K pool]	63.908	84.218	90.683	90.34	93.714
SSDCM [SAG pool]	66.574	83.176	92.859	90.878	93.015
SSDCM [ASAP pool]	66.365	85.064	91.782	90.844	94.689
SSDCM [cluster aware graph summary]	**67.796**	**88.324**	**94.988**	**92.195**	**96.261**

Table: Novelty of cluster-based graph summary

Conclusions

1. Our novel approach, SSDCM, incorporates a unique InfoMax based learning strategy to maximize the MI between local and contextualized global graph summaries for effective joint modeling of nodes and clusters.
2. It improves over the state-of-the-art in four distinct downstream tasks, namely, classification, clustering, visualization, and similarity search.

References

[1] C. Park, D. Kim, J. Han, and H. Yu, "Unsupervised attributed multiplex network embedding.," in *AAAI*, pp. 5371–5378, 2020.

[2] D. Luo, J. Ni, S. Wang, Y. Bian, X. Yu, and X. Zhang, "Deep multi-graph clustering via attentive cross-graph association," in *WSDM*, pp. 393–401, 2020.

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