D^2-GCN: A Graph Convolutional Network with Dynamic Disentanglement for Node Classification

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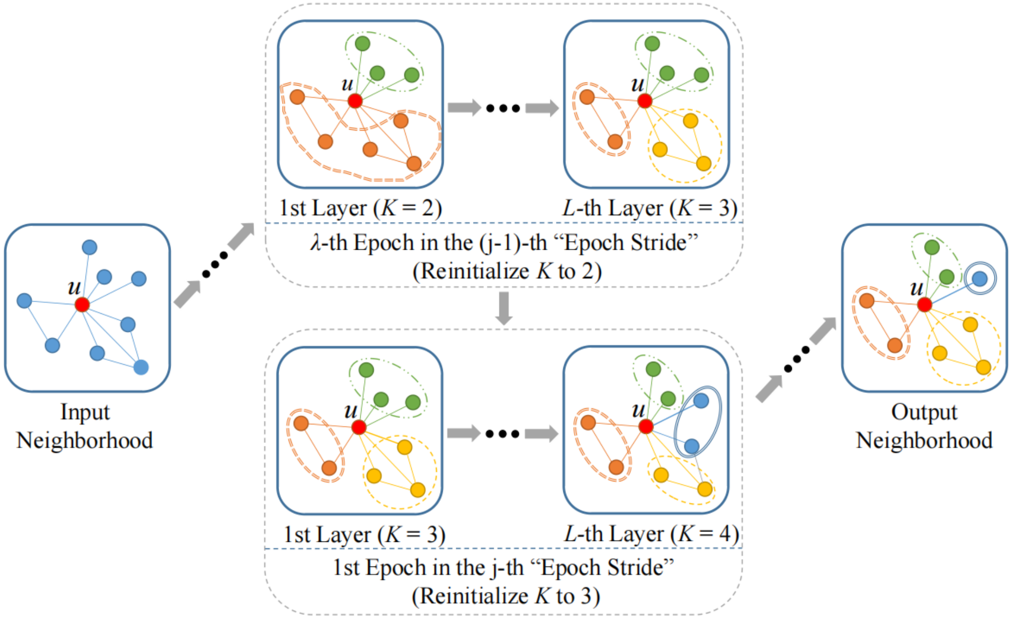
Frontiers of Computer Science, DOI: 10.1007/s11704-023-3339-7

Problems & Ideas

- Problems of conventional graph convolutional networks:
  - Node representations are learned holistically, which ignores the distinct impacts from different neighbors.
  - Current disentangling methods do not try to figure out how many inherent factors the model should assign to help extract the best representation of each node.
- Ideas: Two-level dynamic adjustment of the number of each node's disentangled feature channels during training.



Architecture of D^2-GCN with two-level disentanglement during training, i.e., the epoch level and the layer level.

Main Contributions

- Contributions:
  - A novel disentangled GCN to dynamically adjust the number of each node's disentangled feature channels during training, which helps obtain adaptive node representations on datasets in various fields;
  - A two-level disentangling mechanism that integrates epoch-level and layer-level disentanglement, which helps capture nuanced changes in node representations on graphs of varying sizes or complexities;
  - An information entropy based mechanism to portray the convergence speed of the proposed dynamic disentanglement.

Model	Dataset		
	Cora	Citeseer	Pubmed
MLP [38]	55.1±0.25	46.5±0.33	71.4±0.46
ManiReg [39]	59.5±0.18	60.1±0.24	70.7±0.31
SemiEmb [40]	59.0±0.23	59.6±0.21	71.1±0.28
LP [41]	68.0±0.13	45.3±0.22	63.0±0.26
DeepWalk [35]	67.2±0.11	43.2±0.32	65.3±0.36
ICA [42]	75.1±0.23	69.1±0.26	73.9±0.31
Planetoid [43]	75.7±0.22	64.7±0.19	77.2±0.30
ChebNet [44]	81.2±0.12	69.8±0.23	74.4±0.25
GCN [1]	81.5±0.17	70.3±0.23	79.0±0.42
MoNet [45]	81.7±0.24	71.4±0.27	78.8±0.35
GAT [34]	83.0±0.15	72.5±0.18	79.0±0.22
MixHop [46]	82.3±0.23	72.1±0.18	81.0±0.26
DisenGCN [18]	83.2±0.20	71.5±0.25	79.9±0.19
IPGDN [19]	83.9±0.15	72.8±0.19	80.7±0.21
D^2-GCN	**85.4±0.11**	**73.5±0.12**	**81.8±0.14**

	Model	Dataset			
		PPI	POS	BlogCatalog	Flickr
Macro-F1	DeepWalk	17.8±0.19	11.9±0.21	23.1±0.24	15.3±0.26
	LINE	17.3±0.25	11.8±0.18	22.8±0.27	19.7±0.15
	node2vec	17.9±0.19	12.9±0.25	23.6±0.31	22.4±0.27
	GCN	17.7±0.16	20.1±0.20	24.4±0.28	27.2±0.18
	GAT	19.2±0.13	16.1±0.22	26.8±0.25	30.6±0.23
	DisenGCN	21.4±0.17	26.5±0.21	28.9±0.15	34.2±0.14
	D^2-GCN	**22.3±0.11**	**27.8±0.14**	**29.6±0.12**	**35.7±0.17**
Micro-F1	DeepWalk	20.7±0.20	49.3±0.22	38.8±0.26	30.6±0.17
	LINE	21.1±0.23	49.0±0.16	38.5±0.24	34.2±0.19
	node2vec	20.6±0.17	49.9±0.22	39.0±0.28	38.4±0.31
	GCN	20.7±0.18	50.9±0.18	35.9±0.25	44.3±0.12
	GAT	22.3±0.14	50.7±0.16	39.7±0.22	46.5±0.23
	DisenGCN	25.7±0.18	54.1±0.21	41.8±0.16	49.2±0.16
	D^2-GCN	**26.6±0.15**	**55.4±0.11**	**42.7±0.14**	**50.9±0.15**

Test accuracy results of D^2-GCN and all the baseline methods. Left: node classification on single-label datasets; Right: node classfication on multi-label datasets.