Graph Random Neural Networks for Semi-Supervised Learning on Graphs

Wenzheng Feng, Jie Zhang, Yuxiao Dong Yu Han, Huanbo Luan, Qian Xu, Qiang Yang, Evgeny Kharlamov, Jie Tang

Motivation

The assumption of homophily :adjacent nodes tend to have similar features and labels



Graph Data

stacking many GNN layers tends to make nodes'features indistinguishable

over-smoothing

Naturally, the deterministic propagation makes each node highly dependentbwith its (multi-hop) neighborhoods, leaving the nodes to be easily misguided by potential data noise and susceptible to adversarial perturbations.

not robust to graph attacks

Graph Random Neural Network



Random remove node vector :
$$\widetilde{\mathbf{X}}_i = \epsilon_i \cdot \mathbf{X}_i$$
 $\epsilon_i \sim Bernoulli(1-\delta)$

Data Augmentation :

$$\overline{\mathbf{X}} = \overline{\mathbf{A}}\widetilde{\mathbf{X}}$$
 $\overline{\mathbf{A}} = \sum_{k=0}^{K} \frac{1}{K+1} \hat{\mathbf{A}}^k$

Train model :

$$\widetilde{\mathbf{Z}}^{(s)} = f_{mlp}(\overline{\mathbf{X}}^{(s)}, \Theta),$$

Supervised Loss:

$$\mathcal{L}_{sup} = -\frac{1}{S} \sum_{s=1}^{S} \sum_{i=0}^{m-1} \mathbf{Y}_{i}^{\top} \log \widetilde{\mathbf{Z}}_{i}^{(s)}.$$

Consistency Regularization Loss:

$$\overline{\mathbf{Z}}_{ij}' = \overline{\mathbf{Z}}_{ij}^{\frac{1}{T}} / \sum_{c=0}^{C-1} \overline{\mathbf{Z}}_{ic}^{\frac{1}{T}}, (0 \le j \le C-1),$$

$$\mathcal{L}_{con} = \frac{1}{S} \sum_{s=1}^{S} \sum_{i=0}^{n-1} \|\overline{\mathbf{Z}}_{i}^{'} - \widetilde{\mathbf{Z}}_{i}^{(s)}\|_{2}^{2}.$$

Algorithm 1 GRAND

Input:

Adjacency matrix $\hat{\mathbf{A}}$, feature matrix $\mathbf{X} \in \mathbb{R}^{n \times d}$, times of augmentations in each epoch S, DropNode/dropout probability δ , learning rate η , an MLP model: $f_{mlp}(\mathbf{X}, \Theta)$.

Output:

Prediction Z.

- 1: while not convergence do
- 2: for s = 1 : S do
- 3: Pertube the input: $\widetilde{\mathbf{X}}^{(s)} \sim \text{DropNode}(\mathbf{X}, \delta)$.
- 4: Perform propagation: $\overline{\mathbf{X}}^{(s)} = \frac{1}{K+1} \sum_{k=0}^{K} \hat{\mathbf{A}}^{k} \widetilde{\mathbf{X}}^{(s)}$.
- 5: Predict class distribution using MLP: $\widetilde{\mathbf{Z}}^{(s)} = f_{mlp}(\overline{\mathbf{X}}^{(s)}, \Theta)$
- 6: end for
- 7: Compute supervised classification loss \mathcal{L}_{sup} via Eq. 1 and consistency regularization loss via Eq. 3.
- 8: Update the parameters Θ by gradients descending: $\Theta = \Theta \eta \nabla_{\Theta} (\mathcal{L}_{sup} + \lambda \mathcal{L}_{con})$
- 9: end while

10: Output prediction \mathbf{Z} via: $\mathbf{Z} = f_{mlp}(\frac{1}{K+1}\sum_{k=0}^{K} \hat{\mathbf{A}}^k \mathbf{X}, \Theta).$

Experiments

Method	Cora	Citeseer	Pubmed		
GCN 20	81.5	70.3	79.0		
GAT 35	83.0±0.7	72.5 ± 0.7	79.0 ± 0.3		
APPNP 21	83.8±0.3	71.6 ± 0.5	79.7 ± 0.3		
Graph U-Net 12	84.4 ± 0.6	73.2 ± 0.5	79.6 ± 0.2		
SGC 39	81.0 ± 0.0	71.9 ± 0.1	78.9 ± 0.0		
MixHop [1]	81.9 ± 0.4	71.4 ± 0.8	80.8 ± 0.6		
GMNN 31	83.7	72.9	81.8		
GraphNAS [13]	84.2 ± 1.0	73.1±0.9	79.6±0.4		
GraphSAGE 17	78.9±0.8	67.4±0.7	77.8±0.6		
FastGCN 7	81.4±0.5	$68.8 {\pm} 0.9$	77.6 ± 0.5		
VBAT 9	83.6±0.5	74.0 ± 0.6	79.9±0.4		
G ³ NN 25	82.5 ± 0.2	74.4 ± 0.3	77.9 ±0.4		
GraphMix 36	83.9±0.6	74.5 ± 0.6	81.0 ± 0.6		
DropEdge 32	82.8	72.3	79.6		
GRAND_dropout	84.9±0.4	75.0±0.3	81.7±1.0		
GRAND_DropEdge	84.5±0.3	74.4 ± 0.4	80.9 ± 0.9		
GRAND_GCN	84.5±0.3	74.2 ± 0.3	80.0 ± 0.3		
GRAND_GAT	84.3±0.4	73.2 ± 0.4	79.2 ± 0.6		
GRAND	85.4±0.4	75.4±0.4	82.7±0.6		
w/o CR	84.4±0.5	73.1±0.6	80.9±0.8		
w/o mDN	84.7 ± 0.4	74.8 ± 0.4	81.0 ± 1.1		
w/o sharpening	84.6 ± 0.4	72.2 ± 0.6	81.6 ± 0.8		
w/o CR & DN	83.2±0.5	$70.3 {\pm} 0.6$	78.5 ± 1.4		

Table 1: Overall classification accuracy (%).

Dataset		Cora			Citeseer			Pubmed	
Label Rate	1%	3%	5%	1%	3%	5%	0.1%	0.3%	0.5%
GCN	62.8±5.3	76.1±1.9	79.6±2.1	63.4±2.9	$70.6{\pm}1.7$	$72.2{\pm}1.1$	71.5±2.1	$77.5{\pm}1.8$	$80.8{\pm}1.5$
GAT	64.3±5.8	77.2±2.4	80.8±2.1	64.4±2.9	70.4±1.9	72.0±1.3	72.0±2.1	77.6±1.6	80.6±1.2
GRAND	69.1±4.0	79.5±2.2	83.0±1.6	65.3±3.3	72.3±1.8	73.8±0.9	74.7±3.4	81.4±2.1	83.8±1.3

Table 6: Classification Accuracy under different label rates (%).



Figure 7: GRAND vs. GRAND_dropout.



Figure 2: Generalization on Cora (x: epoch).



Figure 3: Robustness Analysis on Cora.

Figure 4: Over-Smoothing on Cora