Simplifying Graph Convolutional Networks

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Overview

1. GCN Introduction
   - Problems
   - Approaches
2. Simplifying GCN
   - Simplest Formulation
3. Experiments & Results
   - Datasets
   - Results
   - Conclusion

GCN Introduction

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Popular Problems on Graph-Structured Data

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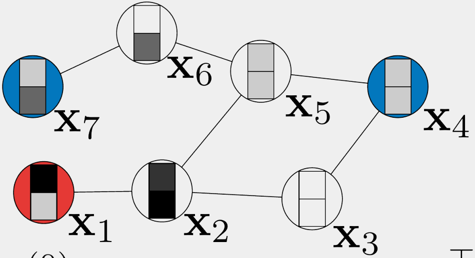
This paper is about classifying vertices

Given a graph structured data $\mathcal{G} = (A, \mathcal{X}, \mathcal{C}, J_{\text{train}}, \mathcal{C})$, we want to find: $\mathcal{C}_i \ \forall i \in V(A) - J_{\text{train}}$.



$$\mathbf{H}^{(0)} = \mathbf{X} = [\mathbf{x}_1, \ldots, \mathbf{x}_n]^\top$$

Figure: Input Graph Example

Graph representation learning:

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- Spectral Clustering [6], Modularity [5]

Approach: Only Use Graph Structure

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Common theme: Graph $\rightarrow$ Surrogate Structure $\rightarrow$ Manifold Learning $\rightarrow$ Node Representaions.

Approach: Graph Structure + Other Information

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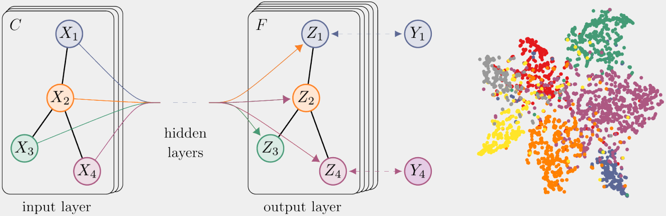
Common theme: Graph + Features $\rightarrow$ Average Features $\rightarrow$ Loss Backpropagation $\rightarrow$ Node Representations.



(a) Graph Convolutional Network

(b) Hidden layer activations

Figure: A Doodle of GCN

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2. Activation: $H^{(k)} = \text{ReLU}(\bar{H}^{(k)}\Theta^{(k)})$
3. Classification: $\hat{Y}_{\text{gcn}} = \text{softmax}(SH^{(K-1)}\Theta^{(K)})$

Simplifying GCN

Simplifying GCN" addresses the excess complexity in recent GCN models.

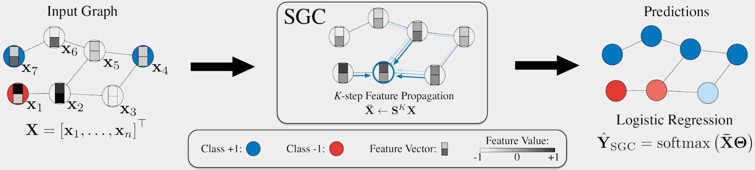

Figure: SGC model

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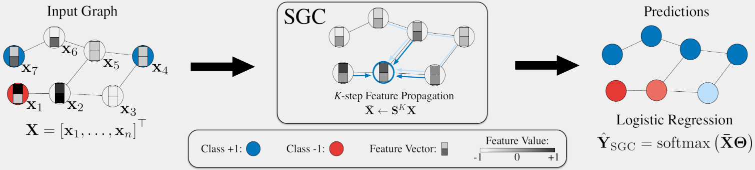

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Main experiment

Input: $\mathcal{G} = (A, \mathcal{X}, \mathcal{C}, J_{\text{train}}, \mathcal{C})$
Output: $\mathcal{C}_i \ \forall i \in V(A) - J_{\text{train}}$

Observation

Hypothesis: Nonlinearity is not important

The main factor in the power of a GNN is the feature averaging step (GCN step 1), *not the nonlinearity between layers* (GCN step 2).

Removing all activation function between K layers:

$$\hat{Y} = \text{softmax}(SS...S\mathcal{X}\Theta^{(1)}\Theta^{(2)}...\Theta^{(K)})$$

Since everything is matrix multiplications:

Simple Graph Convolution

$$\hat{Y}_{\text{sgc}} = \text{softmax}(S^K\mathcal{X}\Theta)$$

Experiments & Results

Datasets

Dataset	# Nodes	# Edges	Train/Dev/Test Nodes
Cora	$2,708$	$5,429$	$140/500/1,000$
Citeseer	$3,327$	$4,732$	$120/500/1,000$
Pubmed	$19,717$	$44,338$	$60/500/1,000$
Reddit	233K	11.6M	152K/24K/55K

Figure: Datasets

Competitors

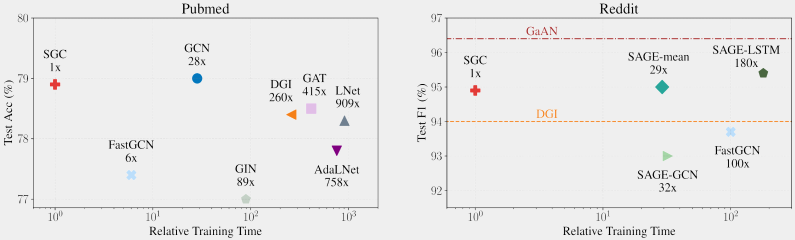

Figure: Competitors and their performance

	Cora	Citeseer	Pubmed
Numbers from literature:			
GCN	81.5	70.3	79.0
GAT	83.0 ± 0.7	72.5 ± 0.7	79.0 ± 0.3
GLN	81.2 ± 0.1	70.9 ± 0.1	78.9 ± 0.1
AGNN	83.1 ± 0.1	71.7 ± 0.1	79.9 ± 0.1
LNet	79.5 ± 1.8	66.2 ± 1.9	78.3 ± 0.3
AdaLNet	80.4 ± 1.1	68.7 ± 1.0	78.1 ± 0.4
DeepWalk	70.7 ± 0.6	51.4 ± 0.5	76.8 ± 0.6
DGI	82.3 ± 0.6	71.8 ± 0.7	76.8 ± 0.6
Our experiments:			
GCN	81.4 ± 0.4	70.9 ± 0.5	79.0 ± 0.4
GAT	83.3 ± 0.7	72.6 ± 0.6	78.5 ± 0.3
FastGCN	79.8 ± 0.3	68.8 ± 0.6	77.4 ± 0.3
GIN	77.6 ± 1.1	66.1 ± 0.9	77.0 ± 1.2
LNet	$80.2 \pm 3.0^{\dagger}$	67.3 ± 0.5	$78.3 \pm 0.6^{\dagger}$
AdaLNet	$81.9 \pm 1.9^{\dagger}$	$70.6 \pm 0.8^{\dagger}$	$77.8 \pm 0.7^{\dagger}$
DGI	82.5 ± 0.7	71.6 ± 0.7	78.4 ± 0.7
SGC	81.0 ± 0.0	71.9 ± 0.1	78.9 ± 0.0

(a) Classic Datasets for GNNs

Setting	Model	Test F1
Supervised	GaAN	96.4
	SAGE-mean	95.0
	SAGE-LSTM	95.4
	SAGE-GCN	93.0
	FastGCN	93.7
	GCN	**OOM**
Unsupervised	SAGE-mean	89.7
	SAGE-LSTM	90.7
	SAGE-GCN	90.8
	DGI	94.0
No Learning	Random-Init DGI	93.3
	SGC	94.9

(b) Reddit Dataset

Figure: Results for SGC

Conclusion

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The authors have demonstrated:

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1. The activations might not be needed between graph layers.

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The authors have demonstrated:

1. The activations might not be needed between graph layers.
2. Simple formulation can give fast and high accuracy results.

Thanks for listening!

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