Similar Idea and Method

Both papers propose to apply graph convolution as a low-pass filter on the feature matrix of graph nodes and then use a fully connected network for node classification. The only difference is the number of network layers.

In the abstract of SGC:

"In this paper, we reduce this excess complexity (of **GCN**) through successively **removing nonlinearities** and collapsing weight matrices between consecutive layers. We theoretically analyze the resulting linear model and show that it corresponds to a fixed low-pass filter followed by a linear classifier."

In our section 4.1:

"Interestingly, by **removing the activation function** ReLU in Eq. (9), we can see that **GCN** is a special case of our GLP, …."

In our section 3:

"GLP consists of two steps. First, a low-pass, linear, shift-invariant graph filter G is applied on the feature matrix X to … The next step is to train a supervised classifier (e.g., multilayer perceptron, convolutional neural networks, support vector machines, etc.) …"

Similar Theoretical Analysis

(1) Both papers show the low-pass property of the adopted filters and demonstrate that the "renormalization trick" in GCN (Kipf & Welling 2017) can shorten the range of the eigenvalues of graph Laplacian.

In section 3 of SGC:

"We demonstrate that SGC corresponds to a fixed filter on the graph spectral domain. In addition, we show that adding self-loops to the original graph, i.e. the renormalization trick (Kipf & Welling, 2017), effectively shrinks the underlying graph spectrum."

In our section 4.1:

"The graph convolution in each layer of the GCN model actually performs feature smoothing with a low-pass filter."

In section 3.2 of SGC:

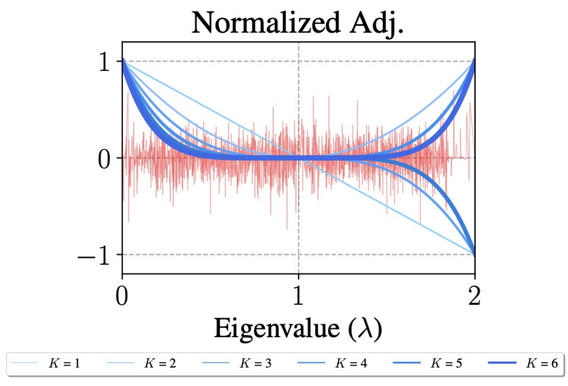
"By adding self-loops, the largest eigenvalue shrinks from 2 to approximately 1.5 and then ..."

In our section 4.1:

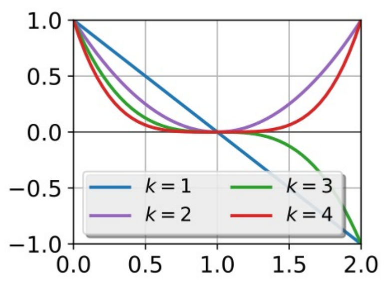
"... by adding a self-loop to each vertex, the range of eigenvalues shrink from [0, 2] to [0, 1.5], thus ..."

(2) The middle sub-figure of Figure 2 in SGC shows the same frequency response functions as our Figure 1(b), with a same parameter k. The difference is that they show two more cases of $k = 5, 6$.

The middle sub-figure of Figure 2 in SGC:



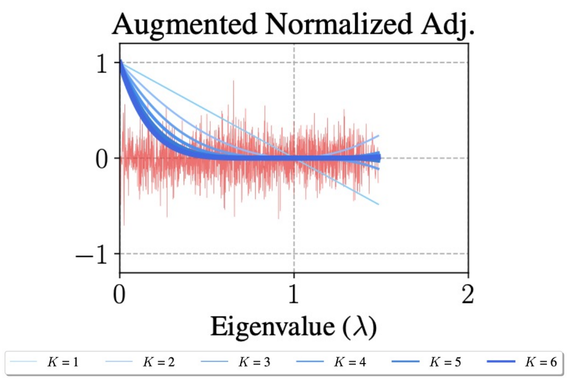
Our Figure 1(b):



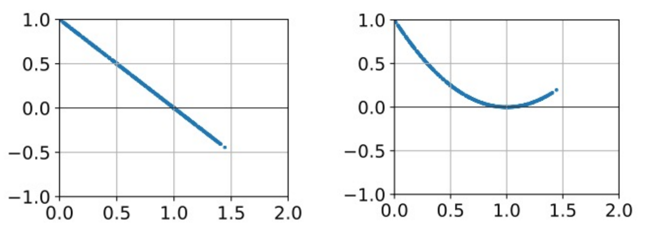
(b) RNM: $(1-\lambda)^k$

(3) The right sub-figure of the Figure 2 in SGC is a combination of our Figure 2(b) and 2(d). The only difference is that we only display two cases $(k = 1,2)$ while they show six cases $(k = 1,2,3,4,5,6)$.

The right sub-figure of Figure 2 in SGC:



Our Figure 2(b) and 2(d):

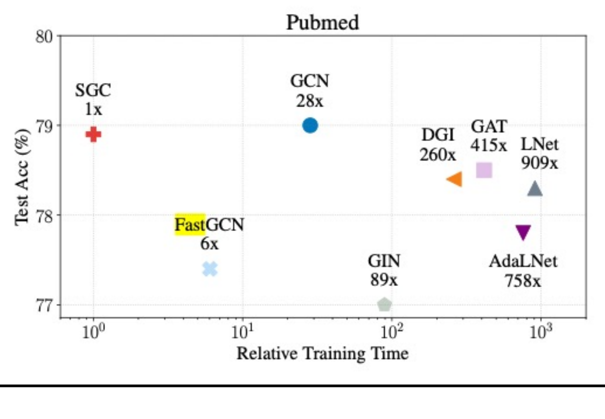


(b) $1-\tilde{\lambda}$ (d) $(1-\tilde{\lambda})^2$

Similar Experimental Design

(1) In addition to reporting classification accuracy on three citation networks, both papers demonstrate a great improvement in training time. SGC observed 28x speedup over GCN on PubMed, while we observed 32x speedup and provided an analysis of computational complexity.

The comparison of training time in SGC (Figure 3):



The comparison of training time in our GLP:

Table 1: Classification Accuracy and running time on

Label Rate	20 labels per class			4 labels per class		
	Cora	CiteSeer	PubMed	Cora	CiteSeer	PubMed
ManiReg	59.5	60.1	70.7	-	-	-
SemiEmb	59.0	59.6	71.7	-	-	-
DeepWalk	67.2	43.2	65.3	-	-	-
ICA	75.1	**69.1**	73.9	62.2	49.6	57.4
Planetoid	75.7	64.7	**77.2**	43.2	47.8	64.0
MLP	56.7 (0.5s)	55.9 (0.6s)	69.1 (0.5s)	37.8 (0.5s)	39.6 (0.6s)	57.6 (0.5s)
LP	67.8 (0.4s)	43.9 (0.3s)	66.4 (1.2s)	60.9 (0.1s)	40.0 (0.2s)	62.6 (4.3s)
GCN	**79.5** (1.5s)	**68.7** (2.3s)	**77.2** (16s)	64.0 (1.8s)	56.4 (2.5s)	66.7 (17s)
GLP (RNM, MLP)	**79.1** (0.5s)	67.6 (0.6s)	**77.2** (0.5s)	**68.4** (0.5s)	**57.5** (0.6s)	**67.2** (0.6s)
GLP (RW, MLP)	**79.1** (0.5s)	67.7 (0.6s)	77.0 (0.5s)	**68.5** (0.5s)	**57.6** (0.6s)	**67.2** (0.6s)
GLP (AR, MLP)	**80.3** (0.5s)	**68.3** (0.7s)	**78.3** (0.5s)	**69.4** (0.7s)	**58.3** (0.9s)	**68.7** (0.8s)

(2) Both papers investigate the effect of the filter parameter k on classification accuracy on the three citation networks. The difference is the range and stride of k.

Figure 4 in Appendix C of SGC:

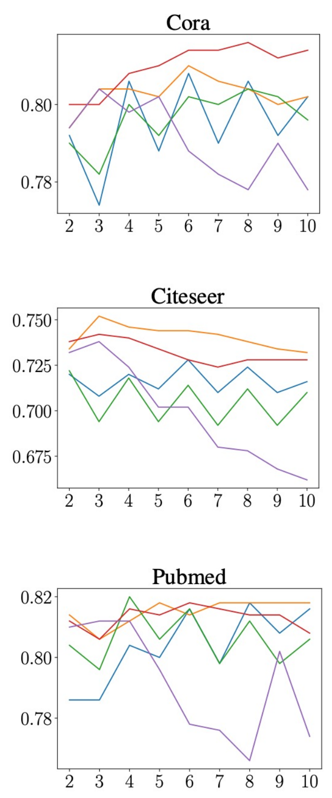


Figure 4. Validation accuracy with SGC using different propagation matrices.

Figure 4,5,6 in our Appendix:

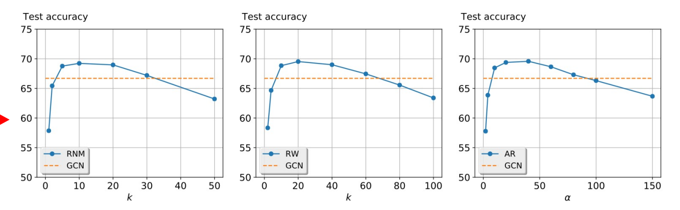


Figure 4: Classification accuracy on Cora with different parameters.

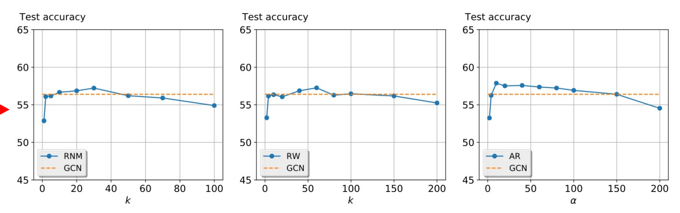


Figure 5: Classification accuracy on CiteSeer with different parameters.

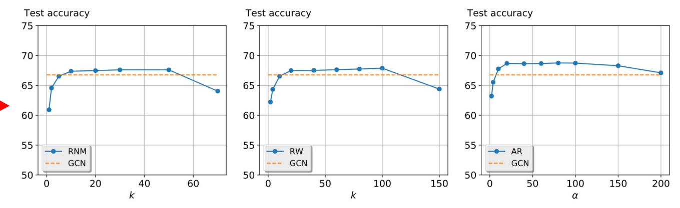


Figure 6: Classification accuracy on PubMed with different parameters.