相同的思路和方法

对方所提出的SGC模型与我方所提出的GLP模型完全相同，即把图卷积看成一个低通滤波器作用在图节点的特征矩阵上，然后使用一个全连接网络直接对图节点分类。唯一不同之处在于双方所使用的全连接网络的层数。

对方摘要：

“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.”

我方章节4. 1：

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

我方第三章：

“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.) …”

相同的理论分析

（1）双方都展示了所用滤波器的低通特性以及GCN (Kipf & Welling 2017)所采用的“renormalization trick”可以压缩图Laplacian的特征值范围。

对方第三章：

“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.”

我方章节4.1：

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

对方章节3.2：

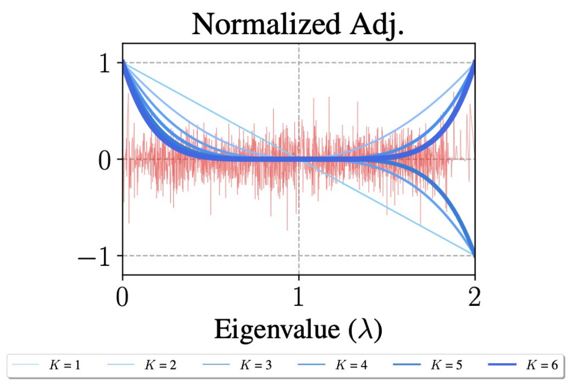
“By adding self-loops, the largest eigenvalue shrinks from 2 to approximately 1.5 and then ...”

我方章节4.1：

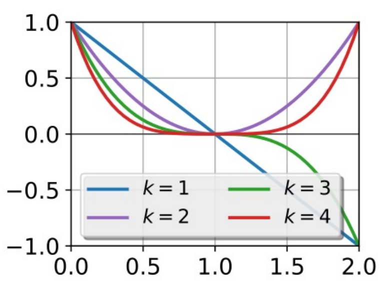
“... by adding a self-loop to each vertex, the range of eigenvalues shrink from [0, 2] to [0, 1.5], thus ...”

（2）对方图2中间子图与我方图1（b）展示了相同的频率响应函数图，且使用了相同的参数符号k。不同之处仅在于对方多展示了$k = 5, 6$ 两种情况。

对方图2中间子图：



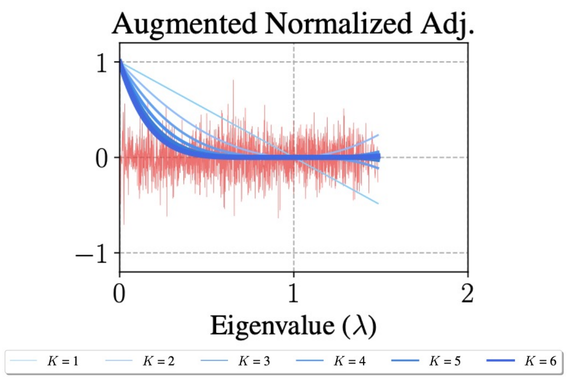
我方图1(b):



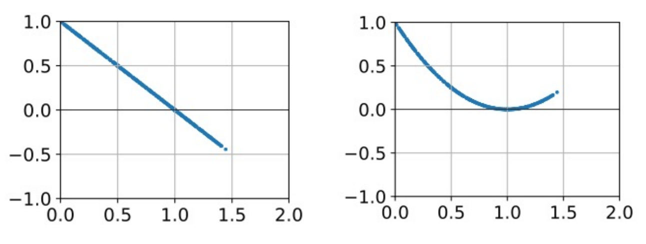
(b) RNM: $(1-\lambda)^k$

（3）对方图2右侧子图为我方图 2(b) 和 2(d) 的叠加。不同之处仅在于我方选取展示了$k = 1,2$ 两种情况，而对方展示了$k = 1,2,3,4,5,6$六种情况。

对方图2右侧子图：



我方图2(b)和2(d):

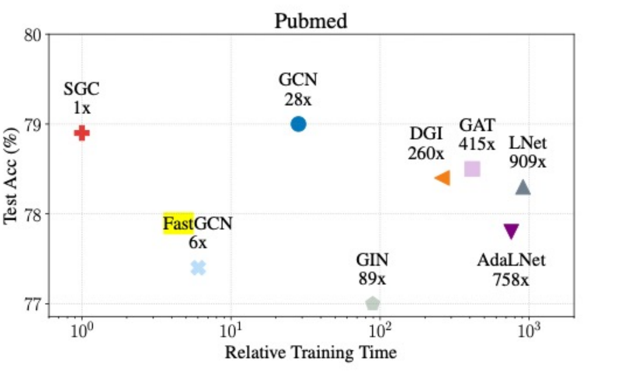


(b) $1-\tilde{\lambda}$ (d) $(1-\tilde{\lambda})^2$

相同的实验设计

（1）除了展示在citation networks上的分类准确率，双方都展示了自己方法相对于GCN (Kipf & Welling 2017) 和其他方法的巨大速度优势。虽然形式不同，但是展示的内容本质相同。对方在PubMed数据集上，观察到了高达28倍的加速。我方观察到了高达32倍的加速，并且提供了对计算复杂度的理论分析。

对方训练速度比较 (Figure 3):



我方训练速度比较 (Table 1):

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）对方图4与我方图4、5、6都分别在三个citation networks上展示了滤波器参数k取不同值对分类准确率的影响。不同之处在于k的取值范围和间隔。

对方附录C中图4：

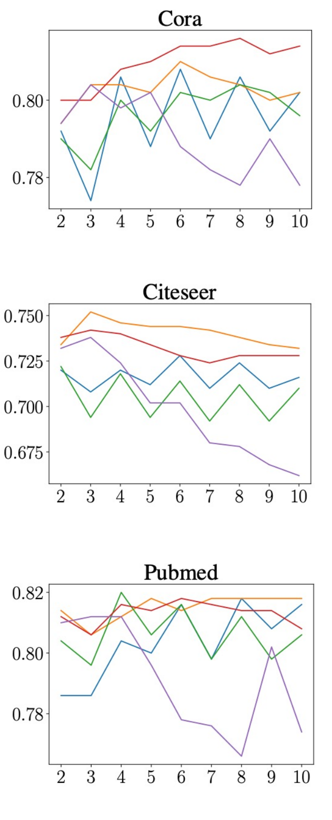


Figure 4. Validation accuracy with SGC using different propagation matrices.

我方附录中的图4、5、6：

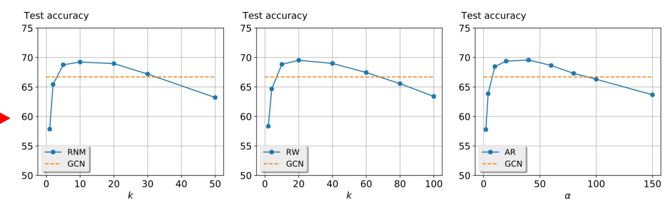


Figure 4: Classification accuracy on Cora with different parameters.

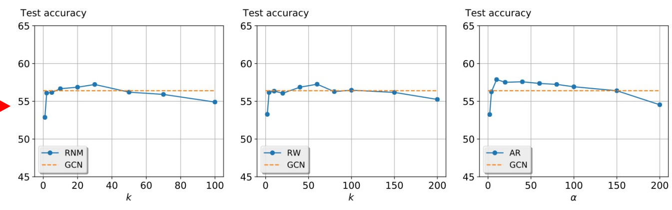


Figure 5: Classification accuracy on CiteSeer with different parameters.

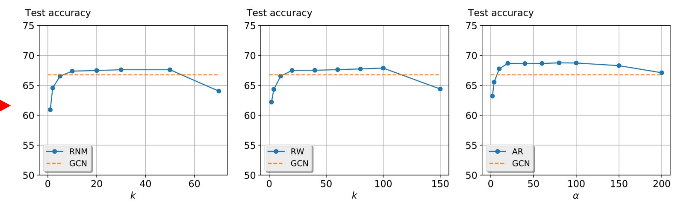


Figure 6: Classification accuracy on PubMed with different parameters.