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A local density optimization method based on a graph convolutional network

Key words: Semi-supervised learning; Graph convolutional network; Graph embedding; Local density

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Motivation

1. GCN ignores some local information at each node in the graph, so data preprocessing is incomplete and the model generated is not accurate enough.
2. Unsupervised graph analysis methods pay more attention to the local adjacency of nodes in the graph, so it is a feasible idea that they can solve the problem and optimize data processing of GCN.
3. When processing GCN data, we do not hope to expand the scale of the original data.

Main idea

1. Feature mapping in the spectral domain is required during training. The mapped matrix is the decomposition matrix of the Laplacian matrix, so we think that adding local features to the Laplacian matrix can achieve the goal.
2. Define the rules of local features to make the nearest local features more important.
3. When calculating the high-order matrix, we can adjust the calculation order of each node because the calculation is synchronous.

Method

1. Unbalanced method: For the input original matrix, we directly calculate the high-order degree matrix of each node one by one, and then use the degree matrix to calculate the Laplacian matrix.
2. Balanced method: For the original input matrix, we first sort it according to the local density of each node, and then calculate their higher-order matrix.

Major results

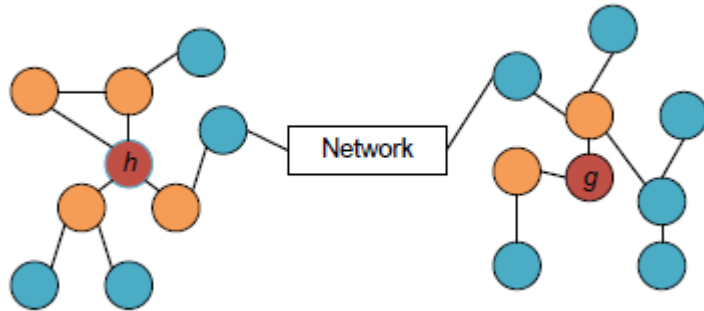


Fig. 1 Difference between the local characteristics of nodes g and h in the rules of local features

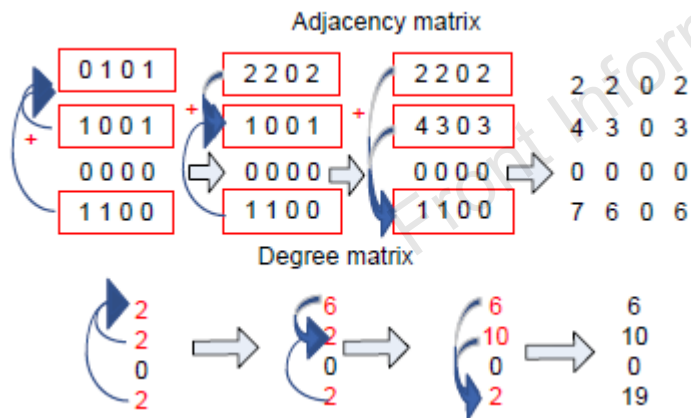


Fig. 2 Calculation process of the second degree matrix in a graph with four nodes

Algorithm 1 Third-order degree matrix computation

Input: adjacency matrix A

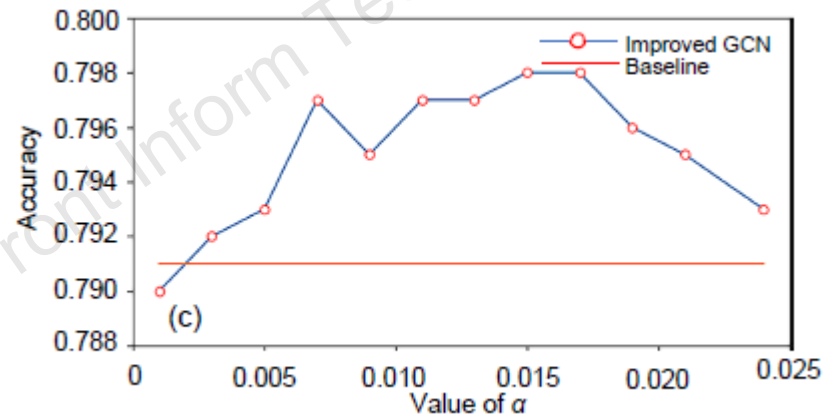
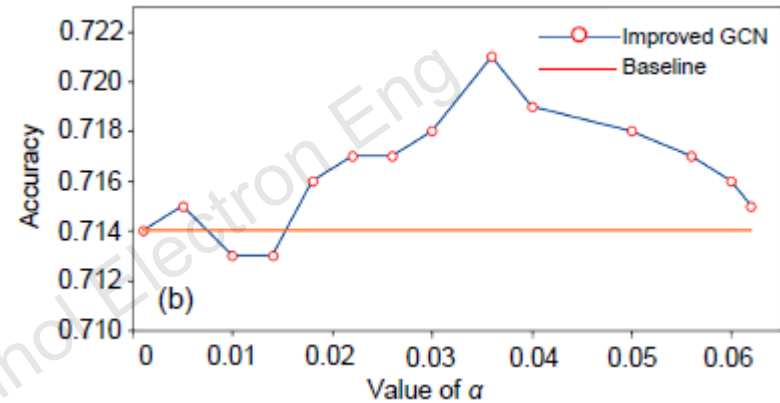
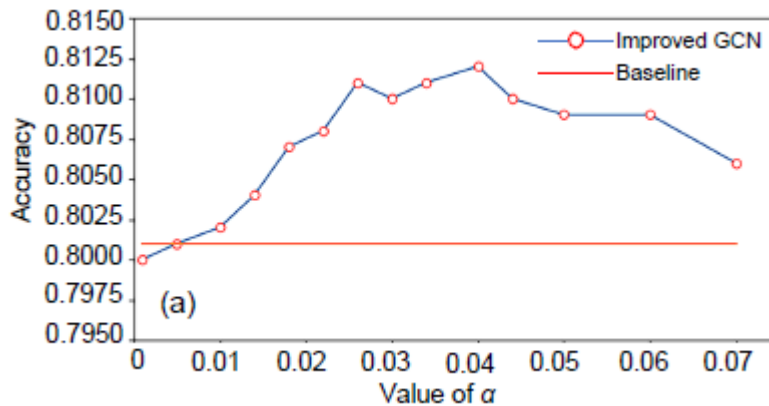
Output: Laplacian matrix L

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1   $D = \text{sum}(A.\text{row})$ 
2  define  $D_2$  and  $D_3$ 
3   $D_2, D_3 = D$ 
4  for  $A_i$  in  $A$ 
5      for  $A_{ij}$  in  $A_i$ 
6          if nodes  $v_i$  and  $v_j$  are connected do
7              calculate  $D = D + \alpha_1 D_2$ 
8              for  $A_{jk}$  in  $A_j$ 
9                  if nodes  $v_j$  and  $v_k$  are connected do
10                     calculate  $D = D + \alpha_2 D_3$ 
11                 end if
12             end for
13         end if
14     end for
15 end for
16 calculate  $L = D^{-1/2} A D^{-1/2}$ 
17 return matrix  $L$ 

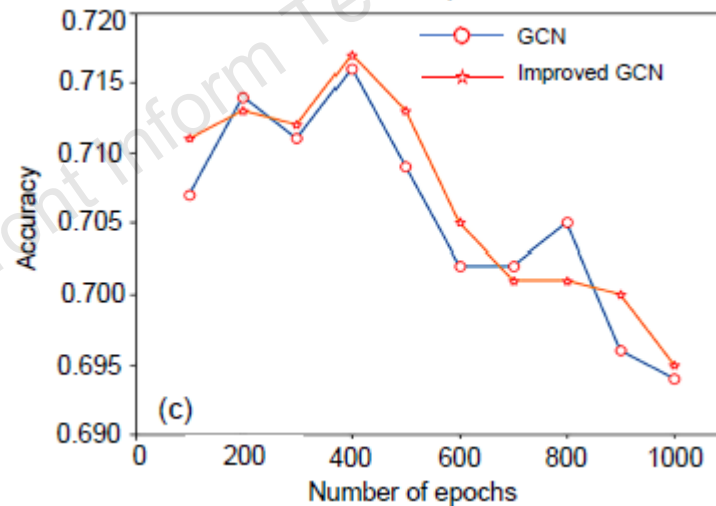
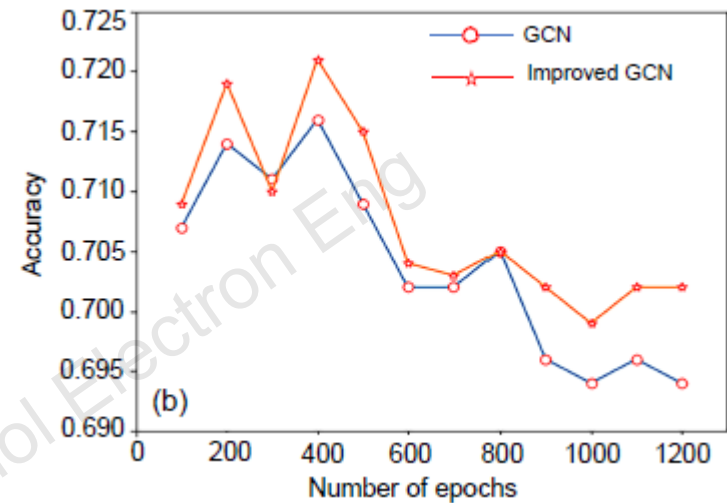
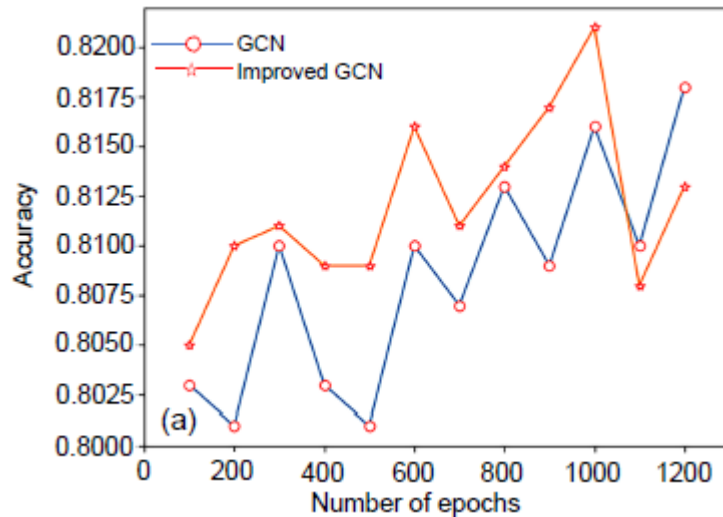
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Major results (Cont'd)



Node classification prediction accuracy on the Cora (a), Citeseer (b), and Pubmed (c) datasets with changing α

Major results (Cont'd)



Node classification prediction accuracy on the Cora (a), Citeseer (b), and Pubmed (c) datasets with different numbers of epochs

Major results (Cont'd)

Table 8 Comparison of our LDGCN algorithm and five mainstream algorithms in terms of classification accuracies

Method	Accuracy		
	Cora	Citeseer	Pubmed
SemiEmb	0.590	0.596	0.717
DeepWalk	0.672	0.432	0.653
Planetoid	0.757	0.647	0.619
GCN	0.815	0.703	0.790
Graphite	0.821	0.710	0.793
LDGCN	0.819	0.721	0.798

Best results are in bold

Conclusions

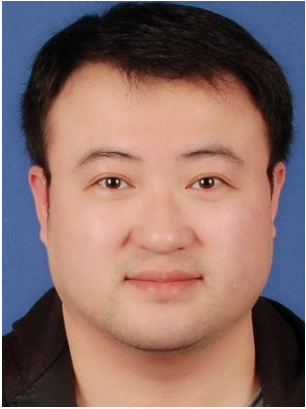
1. The existence of the extreme values indicates that the optimal coordination parameters are related to the dataset.
2. This optimization of input data is not affected by the epoch size.
3. When using different orders, the higher the order, the smaller the improvement of the algorithm, and the more time it takes to calculate the variable.
4. This improvement means that the focus of a GCN can move slightly into the graph structure like the unsupervised model.



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Tie-hu FAN received his BS and MS degrees from the School of Computer Science and Technology of Jilin University in computer science and technology in 2013 and 2006, respectively, and his PhD degree in computer intelligent control from Jilin University in 2010. He is now an associate professor. His major research interests include intelligent control, computational intelligence, and embedded operating systems.



Ming-hui SUN received his PhD degree in computer science from the Kochi University of Technology, Japan, in 2011. He is currently an associate professor in the College of Computer Science and Technology in Jilin University, China. He is interested in using HCI methods to solve challenging real-world computing problems in many areas, including tactile interface, pen-based interface, and tangible interface.