View Reviews

Paper ID
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Paper Title
Tackling Over-Smoothing: Graph Hollow Convolution Network with Topological Layer Fusion

Reviewer #1

Questions

1. Summarize the paper's main contribution and impact.
The paper studies the oversmoothing problem of graph neural networks (GNNs). The authors claim the following contributions: (1). Some unique insight for over-smoothing, described as topological expressiveness loss as a result of over-densifying; (2). A novel framework called Graph Hollow Convolution Network, which is built upon two ideas: (i) hollow filters and (ii) topological layer fusion.

2. List three, or more, strong aspects of this paper. Please number each point.
(1) Oversmoothing is a hot and important topic in the research area of graph neural networks.

(2) The paper has proposed a new method to tackle the oversmoothing problem.

(3) Experiments have been conducted.

3. List three, or more, weak aspects of this paper. Please number each point.
(1) The insight for over-smoothing, described as topological expressiveness loss as a result of over-densifying, does not bring much additional value on top of the known results for oversmoothing in the literature.

(2) The proposed method is lacking in-depth technical analysis and has some limitations.

(3) The experiment setup is unclear and the experiments are not sufficient (see more details below).

4. Detailed comments to the authors.
The paper is generally well-structured and easy to follow. But I have some concerns about the contributions claimed in the paper.

(1) The oversmoothing issue has been well studied in the literature, particularly in relating to the WL algorithm. The discussion of oversmoothing from the perspective of over-densifying is lacking of theoretical depth and novelty, and doesn't contribute much new insights for the issue.

(2) The proposed method aims to filter out the nodes that have been previously propagated (i.e., the key idea of hollow filters). However, this may lead to loss of expressiveness in identifying local structures such as cycles. Several papers in the literature have discussed the expressiveness of GNNs using unique identifiers or random features but allowing propagating through nodes repeatedly, e.g.,

Identity-aware graph neural networks,You, Jiaxuan and Gomes-Selman, Jonathan and Ying, Rex and Leskovec, Jure. AAAI 2021.

Further, this kind of filtering may not necessarily alleviate the oversmoothing issue. The performance could also depend on the label distribution of neighboring nodes. The paper doesn't provide in-depth discussion in these aspects.

(3) The experiments should include an ablation study to show the impacts from hollow filters and topological layer fusion separately.

It is also unclear which setting of data split the authors have used? Are they the standard splits as suggested in Kipf & Welling (2017), or the random splits used in Pei et al. (2020)?

How does the method perform on OGB datasets?

Open graph benchmark: Datasets for machine learning on graphs. Hu et al., NeurIPS 2020.

The results of Fig. 2 are unclear. Which dataset is used? If the dataset is Cora, then the results would be inconsistent with the results presented in the original paper of GCN, which has the best performance when the number of layers is 2.

5. Relevance.
Relevant

6. Novelty of the paper.
Less Novel

7. Overall Recommendation.
Weak Reject

8. Justification to your overall recommendation.
The technical contributions of the paper are marginal. The experiments are not convincing. The paper needs more work to improve the quality.

9. What is your confidence in your review of this paper?
High (I have previous/current work in this area)

10. Would you nominate this paper for the Best Paper Award?
No

Reviewer #2

Questions

1. Summarize the paper's main contribution and impact.
This paper proposed a new graph convolutional neural network based on a new graph convolution layer. The proposed convolution is designed based on spanning tree expansion, which can relieve over-smoothing problem. Numerical experiments demonstrated the effectiveness of the new convolutional layer against over-smoothing layers.

2. List three, or more, strong aspects of this paper. Please number each point.
The idea of the new convolutional layer is simple and effective.

Experimental design is suitable to demonstrate the effectiveness.

3. List three, or more, weak aspects of this paper. Please number each point.
The detail of the model and calculation would be difficult to understand.

Some parts of numerical experimental procedures would be unclear.

4. Detailed comments to the authors.
The proposed method is interesting. And experimental result is reasonable. However, some parts of paper presentation should be improved.

The problem setting of Figure 2 is unclear. What dataset this experiment used should be mentioned. If it used synthetic data, the detailed generation procedure should be described.

I guess that Eq (1) would be incorrect since the definition is inconsistent to Figure 3. From the definition, node 7 in the rightest tree has a child of node 6. And a^k_{i,j} is not defined before Eq (1).

The variable W_k in Eq (2) is not defined. The index of products in Eq (4) is unnatural.

The procedure of the case study in 4.4 is unclear. How to use MDS for the experiments should be described in more details.

5. Relevance.
Highly Relevant

6. Novelty of the paper.
Novel

7. Overall Recommendation.
Weak Reject

8. Justification to your overall recommendation.
This paper is interesting, but it is not easy to understand.

9. What is your confidence in your review of this paper?
Medium (I have worked in a related area)

10. Would you nominate this paper for the Best Paper Award?
No

Reviewer #3

Questions

1. Summarize the paper's main contribution and impact.
This paper investigates the performance degradation of deep GCNs and identifies the key factor of over-smoothing which is the topological expressive- ness loss when the stacked graph diffusion operators are over-densifying in deep layers.
The authors proposed the Graph Hollow Convolution Network to retain the expressiveness of the topological information and integrate information from different layers and emphasize graph topology information

2. List three, or more, strong aspects of this paper. Please number each point.
1) a dedicatedly designed convolutional layer that applies a hollow filter on the stacked graph diffusion operator to retain the expressiveness of the topological information in deep layers;
2) the topological layer fusion that strengthens the final representations by coherently incorporating information from different layers based on graph topology structure.
3) Extensive experiments on benchmark datasets show that the proposed method outperforms the state-of-the-art methods and effectively relieves the over-smoothing problem.

3. List three, or more, weak aspects of this paper. Please number each point.
1. The datasets used in this paper were small and all of them only come from two domains.
2. there is not enough analysis of comparison of the proposed method with off-the-shelf methods of addressing over-smoothing issues.
3. some statements need to be polished.

4. Detailed comments to the authors.
Addressing the over-smoothing issue is critical for taking the Graph-based deep-structure models forward a step.
This paper proposed a method to tackle it and experimental results displayed a satisfactory image.
If there are more evidences in more network instances come from various domains, the work will be daintier.

5. Relevance.
Highly Relevant

6. Novelty of the paper.
Novel

7. Overall Recommendation.
Accept

8. Justification to your overall recommendation.
In my opinion, this work is appropriate for the conference.

9. What is your confidence in your review of this paper?
Low (I have not worked in a related area)

10. Would you nominate this paper for the Best Paper Award?
No

Reviewer #5

Questions

1. Summarize the paper's main contribution and impact.
This paper proposed a Graph Hollow Convolution Network (GHCN) that designed a hollow filter applied to the stacked graph diffusion operators for the expressiveness of the topological information, and also integrated information from different layers and emphasized graph topology information using topological layer fusion instead of commonly used concatenation or pooling. Experiments were conducted on multiple benchmark datasets.

2. List three, or more, strong aspects of this paper. Please number each point.
1. A dedicatedly designed convolutional layer that applies a hollow filter on the stacked graph diffusion operator to retain the expressiveness of the topological information in deep layers.
2. Proposed the topological layer fusion strengthens the final representations by coherently incorporating information from different layers based on graph topology structure.

3. List three, or more, weak aspects of this paper. Please number each point.
Regarding Fig.2, why network with the feature only is much better than with topology only or GCN (including both)? even GCN already included feature information its performance decreased significantly, what dominated this? How to know the proposed network is robust? The text did not explain.

4. Detailed comments to the authors.
Regarding Fig.2, why network with feature only is much better than with topology only or GCN (including both)? even GCN already included feature information its performance decreased significantly, what dominated this? How to know the proposed network is robustness? The text did not explain.

5. Relevance.
Relevant

6. Novelty of the paper.
Less Novel

7. Overall Recommendation.
Weak Reject

8. Justification to your overall recommendation.
This paper is straight-forward and easy to understand but it is not from my domain so that I have limited background to evaluate whether the novelty is limited. Experiments have achieved good results on benchmark datasets.

9. What is your confidence in your review of this paper?
Low (I have not worked in a related area)

10. Would you nominate this paper for the Best Paper Award?
No