FAST School of Computing

Submitted by

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Phase 2

1. Abstract:

This research examines how the effectiveness of recommendation models based on network Convolutional Networks (GCNs) might be attributed to their ability to integrate both the structure of the interaction network and user-item interactions. However, these models have two main issues: noise in the interactions causes the models to perform worse and they become overly smooth when too many layers are added. The authors suggest a method known as LayerGCN, which improves layer representations as nodes update and information spreads. They also reduce noise in the interaction network by removing edges according to node degrees. Their model trains quickly and outperforms current ones across multiple datasets, according to experimental results.

2. Problem Statement:

The paper's problem statement focuses on two main problems in Graph Convolutional Network (GCN)-based recommendation models:

1. **Over smoothing**: When too many layers are stacked, over smoothing happens, which reduces performance and causes a loss of discriminative information.
2. **User-item interaction noise**: The accuracy of recommendations might be impacted by bias and uncertainty introduced by noise in the interaction data.

3. Solution:

There are two key components to the suggested solution:

1. **LayerGCN Model:** This improvement tries to increase recommendation accuracy by preventing the loss of discriminative information when more layers are added.
2. **User-Item Interaction Graph Sparsification:** The study suggests sparsifying the interaction graph by removing edges according to node degrees in order to lessen the effects of noise in user-item interactions. By concentrating on the most informative edges and minimising computational complexity, this method seeks to enhance performance and training convergence.

4. Improvements in the Solution:

1. **Dynamic Adjustment of Layer refining:** Performance and adaptability could be improved by dynamically modifying the refining mechanism in response to the properties of each layer or the graph structure, as compared to uniformly applying a static refinement procedure to all layers.
2. **Robustness to Noise:** Increasing the model's resistance to noise using methods like robust optimisation or adding uncertainty estimates to the recommendation process may help it function better in noisy data scenarios that arise in the real world.
3. **Scalability:** Ensuring the model is scalable, particularly for large-scale recommendation systems, by leveraging methods like model parallelism or distributed computing to effectively manage enormous interaction graphs.

5. Experimental Results

Train Loss Reduction:

- Start: 307,054.5983
- End: 187,007.3885

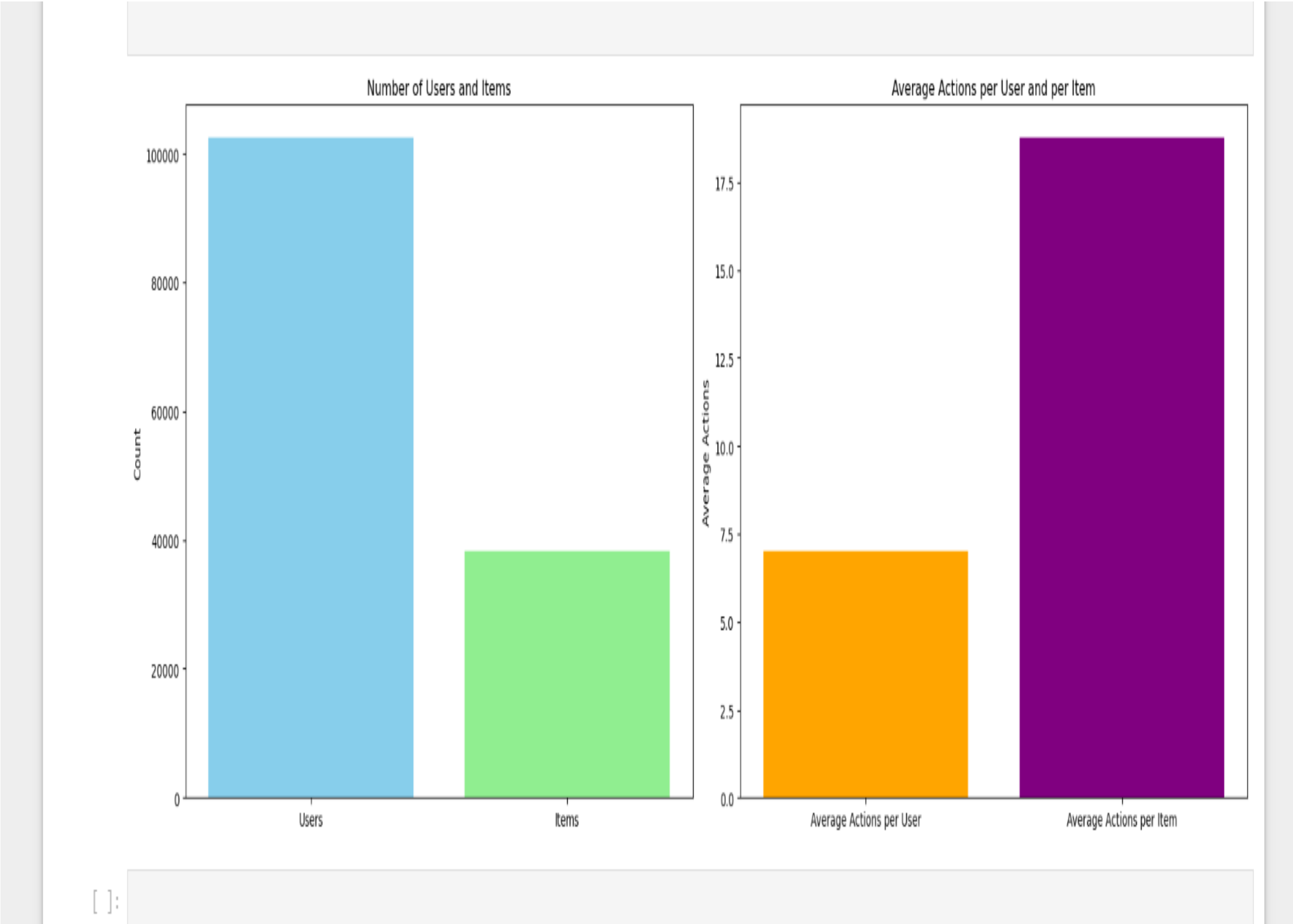
Validation Results (Best):

Metric	**Value**
Recall@5	0.0100
Recall@10	0.0156
Recall@20	0.0252
Recall@50	0.0495
NDCG@5	0.0101
NDCG@10	0.0118
NDCG@20	0.0149
NDCG@50	0.0209
MAP@5	0.0078
MAP@10	0.0081
MAP@20	0.0088
MAP@50	0.0097
Precision@5	0.0073
Precision@10	0.0053
Precision@20	0.0040
Precision@50	0.0028

The model's performance at the conclusion of the training phase is represented by these values. The highest validation scores show how well it matches users with relevant goods. Recall, NDCG, MAP, and precision all showed notable gains for the model, demonstrating its improved capacity to rank pertinent items and generate more precise suggestions.

6- Graph Representation

1. **Data Info.**



2-Final Results