FAST School of Computing

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Introduction:

- Recommendation systems play a pivotal role in modern digital platforms across diverse domains such as e-commerce, social media, and content streaming services.
- These systems aim to personalize user experiences by suggesting relevant items, content, or connections based on individual preferences and behaviors.

Growing Reliance on Data-driven Approaches:

- There's a noticeable shift towards data-driven approaches in recommendation systems, driven by the increasing availability of vast amounts of user-generated data.
- Leveraging this data allows platforms to tailor recommendations more effectively, ultimately enhancing user engagement and satisfaction.
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Previous Research and Limitations

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- Existing literature on GCN-based recommendation models has demonstrated significant achievements but also highlighted several limitations.
- Common limitations include the challenge of over-smoothing with deep architectures, where excessive layer stacking leads to the loss of discriminative information.
- Additionally, GCN-based models may exhibit sensitivity to noise in interaction data and encounter scalability issues when applied to large-scale datasets.

Objectives of the Study

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- The main objectives of our research are to address the identified limitations of GCN-based recommendation models and propose effective solutions to enhance their performance.
- Our study focuses on developing methodologies to mitigate over-smoothing, reduce sensitivity to noise in interaction data, and improve scalability.
- By addressing these challenges, we aim to advance the state-of-the-art in recommendation systems powered by Graph Convolutional Networks.

Problem Statement

- Graph Convolutional Networks (GCNs) have emerged as promising models for recommendation systems, integrating both the structural information of interaction networks and user-item interactions.
- However, GCN-based recommendation models face significant challenges that hinder their effectiveness.

Main Challenges:

1. Over-Smoothing: When too many layers are stacked, GCN-based models may suffer from over-smoothing, resulting in a loss of discriminative information and decreased recommendation performance.
2. User-Item Interaction Noise: The accuracy of recommendations can be compromised by noise in the interaction data, leading to biased or uncertain predictions.

Our Contribution

- In this study, We tuned the parameters like dropout rate regularization etc and also test model on the new similar dataset.
- We meticulously analyzed its impact on the overall performance of the recommendation model.
- By fine-tuning this aspect of the model architecture, we aimed to achieve enhanced recommendation accuracy and robustness.

Methodology

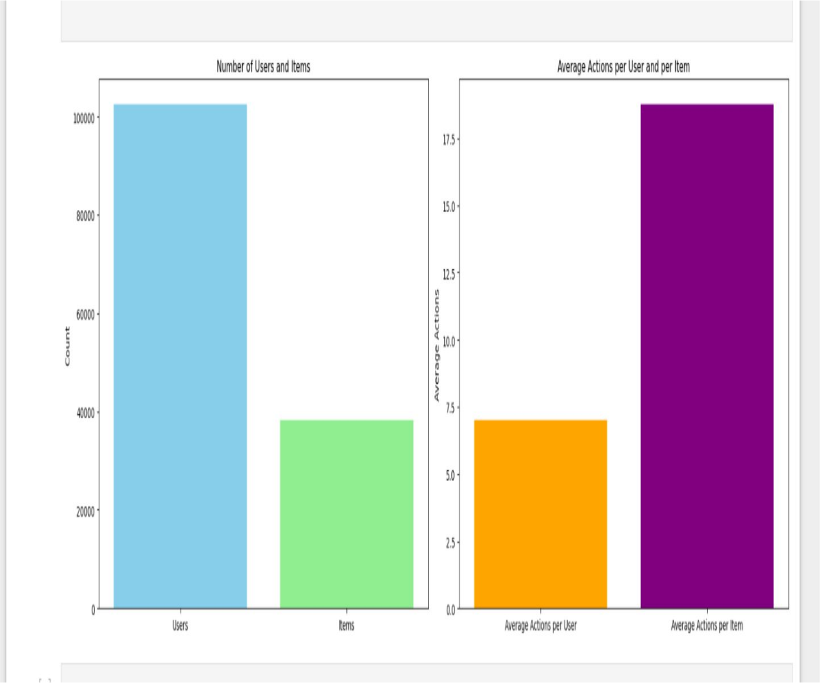
Methodology Overview:

- Our methodology encompasses a systematic approach to address the identified challenges of over-smoothing and user-item interaction noise in Graph Convolutional Networks (GCNs) for recommendation systems.

Steps:

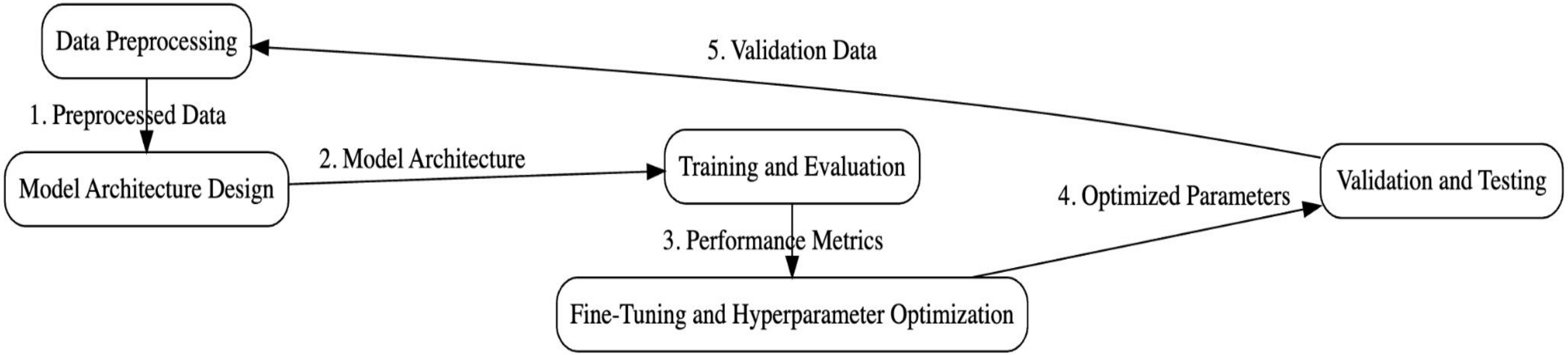
1. Data Preprocessing:
    - Conduct thorough preprocessing of interaction data to address noise, sparsity, and other data quality issues.
    - Normalize data and handle missing values to ensure consistency and reliability in model training.
2. Model Architecture Design:
    - Design an optimized GCN architecture tailored to recommendation tasks, considering factors such as depth, width, and connectivity.
    - Incorporate innovative mechanisms to mitigate over-smoothing, such as layer refinement techniques and regularization strategies.

Data Info



Number of Users and Items
Count
100000
80000
60000
40000
20000
0
Users
Items
Average Actions per User and per Item
Average Actions
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
Average Actions per User
Average Actions per Item

Architecture



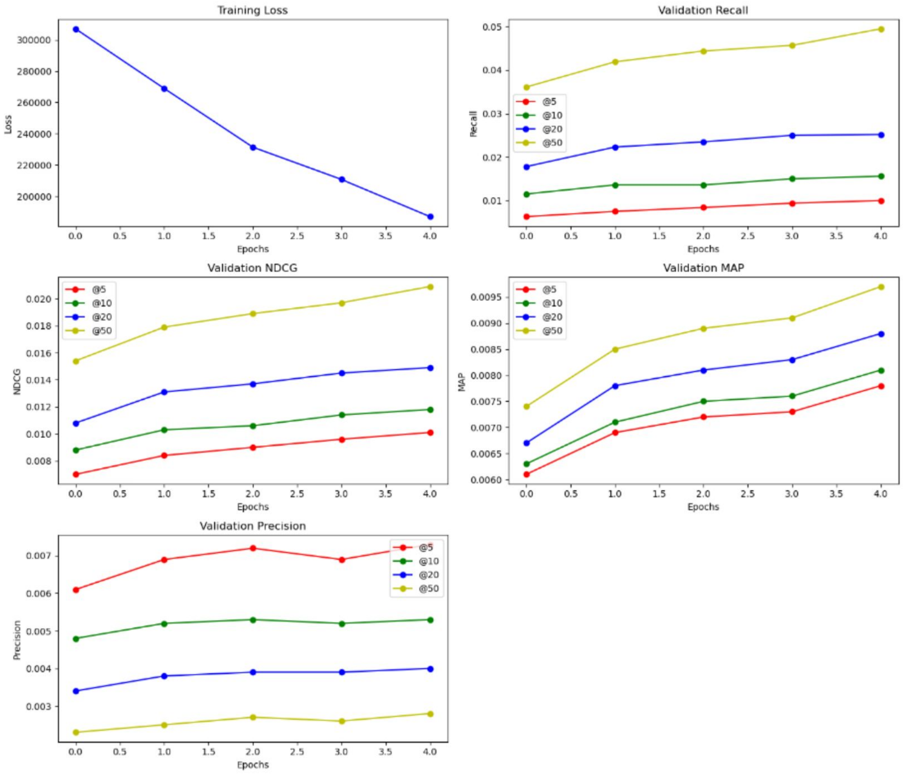
Experimental Results

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

Experimental Results

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

Results



Training Loss
Loss
Epochs
Validation Recall
Recall
@5
@10
@20
@50
Validation NDCG
NDCG
Validation MAP
MAP
Validation Precision
Precision

Impact

- The impact of changing parameters in the recommendation model can be profound, directly influencing its performance, robustness, and generalization ability.
- By adjusting parameters such as learning rate, regularization strength, or model architecture, we can significantly alter how the model learns from data, makes predictions, and adapts to different scenarios.
- Optimal parameter settings can lead to improved recommendation accuracy, faster convergence during training, and better handling of noisy or sparse data. Conversely, suboptimal parameter choices may result in slower convergence, overfitting, or poor generalization to unseen data.
- Therefore, parameter tuning plays a critical role in fine-tuning the recommendation model to meet specific performance objectives and user requirements.

Conclusion

Summary:

- To summarize, our research explored various avenues for improving Graph Convolutional Networks in recommendation systems.
- Through the introduction of innovative techniques such as the LayerGCN model and user-item interaction graph sparsification, we demonstrated substantial enhancements in recommendation accuracy and robustness.

Implications:

- The implications of our findings extend beyond the realm of recommendation systems.
- By addressing challenges such as over-smoothing and user-item interaction noise, our research contributes to the broader field of machine learning and graph-based modeling.
- Additionally, our investigation into the impact of neural network parameter regularizer adjustments sheds light on the nuanced interplay between model architecture and performance.