Rethinking Citation Networks: Directed Graph Convolutions for Accurate Paper Recommendations

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DECLARATION

I, Yujing Ju, confirm that this work submitted for assessment is my own and is expressed in my own words. Any uses made within it of the works of other authors in any form (e.g., ideas, equations, figures, text, tables, programs) are properly acknowledged at any point of their use. A list of the references employed is included.

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ABSTRACT

The growing number of academic papers provides more references for researchers, educators, and educatees. Conversely, it is becoming increasingly difficult to retrieve papers of interest. To address these challenges, Neural Collaborative Filtering, Heterogeneous Graph Neural Network, Graph Attention Network, Deep Q-Network and other widely applied generalized recommendation algorithms are used in paper recommendation and academic search tasks. These algorithms perform well in most cases. However, most of them ignore the directionality of the citation relationship, which may lead to the recommendation model incorrectly capturing the academic relationship between papers. Furthermore, the model may not be able to model the academic paper citation relationship or author-paper relationship network accurately.

In a recommendation model without directional constraints, one potential effect is that the importance of some papers can be overestimated. The introduction of Directed Graph Convolutional Networks has effectively relased this problem. Our work includes node embedding and recommendation results for fusion of Spectrum based directed Graph Convolutional Neural Networks and Heterogeneous Graph Attention Networks. This may not only improve the convolution efficiency by using spectral domain convolution, but also capture the directed paper citation relationship in the academic relational network and the complex interaction relationship between heterogeneous nodes in the author-paper relational network.

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Table of Contents

1 INTRODUCTION

Currently, the importance of researchers seeking relevant and personalized academic papers cannot be overemphasized. However, paper recommendation and academic search systems often rely on Neural Cooperative Filtering[He et al. 2017] and Heterograph Neural Network[Zhang et al. 2019]. Consequently, three essential and pending problems persist: (1)inefficient meta-path[Sun et al. 2011] selection, (2)ignoring the directionality of reference relationships, as well as (3)data sparsity and cold start problem.

As a classic algorithm in recommendation systems, although Neural Collaborative Filtering(NCF)[He et al. 2017] performs well in most applications, its dependency on the users' ratings of the item, such as customer ratings of restaurant meals, leads to data sparsity. This is because the quantity of items with a rating is small. The introduction of Heterograph Neural Network[Zhang et al. 2019] greatly alleviates this situation. HGNN can handle graph structures that contain multiple types of nodes and edges. Therefore, It can easily capture information about different types of user-item interactions, eliminating the need to focus too much on whether an item has a score. Additionally, it can capture higher-order neighbor information through several times of graph convolution. The scarcity of information is gradually being alleviated. All of these are things that NCF cannot do. It also makes it possible to capture information about the interaction between author and paper in academic networks and paper citation relationships. Nevertheless, HGNN still faces the dilemma of inefficient meta-path selection. In heterogeneous information networks, meta-path means the relationship between different types of entities. For example, in the academic network, meta-path can represent the relationship between the Author and the publication meeting (Author → Paper → Venue). It can also represent the cooperative relationship between authors(Author → Paper → Author). The difference in meta-path choice will considerably affect the model effect. But making a reasonable choice is a crucial work.

For academic reference relationships, some recent models use Graph Attention Network(GAT) [Wang et al. 2019] to selectively aggregate neighbor node information during information aggregation. This method allows the higher-order neighbor information associated with the node to be preserved, and the irrelevant interference information can be screened out to the maximum extent. Unfortunately, the GAT model, like HGNN, misses the directivity of reference relationships. Considering a specific condition, An article with low initial impact heavily cites well-known papers in the field. In the recommendation system established by the above two models, due to the undirection of the edges, the paper will accumulate a lot of influence through information aggregation. It is a serious flaw caused by a lack of consideration of the basic concept that referential behavior is directed. In our work, a serious of problems raised by this omission will be heavily considered.

The problems of sparse information and cold start encountered in every recommendation system will be alleviated by our work. Especially for the cold start problem, the correct capture of directed reference relationships will significantly improve the recommendation accuracy.

1.1 Motivation

The specific subject of this dissertation is improving the accuracy of academic paper recommendation. The most notable problem in this field is existing models use artificial assignment to assign weights to different meta paths, which means that their ability to capture semantic information about different types of edges is limited. And they ignore the directivity of reference relationships. in response to this phenomenon, we will use Spectrum based Directed Graph Convolutional Network and Heterogeneous Graphs Attention Network to solve this problem. Spectrum based Directed Graph Convolutional Network can use spectral convolution to improve computational efficiency while capturing direction information among citation relationship network. Heterogeneous Graphs Attention Network can ensure that the complex interactive information in a heterogeneous network composed of author-paper is captured properly, and at the same time, use the attention mechanism to assign weights to different meta-paths flexibly. After that, they will be combined to form a Layer-wise Heterogeneous Network. Firstly, the Spectrum based Directed Graph Convolutional Network is used to deal specifically with single-type nodes (paper nodes). Then global aggregation was carried out through the Heterogeneous Graphs Attention Network. In this way, they will jointly participate in the transmission and aggregation process of node information, to make up for the shortcomings of existing models and improve the accuracy of academic paper recommendation tasks.

1.2 Aim and Objectives

So in this dissertation, we aim to address this aspect of the dependency of meta-path selection and the ignorance of the directionality of reference relationships. In particular, we want to achieve the following objectives:

- Automatically adjusts semantic dependencies to eliminate the need for meta paths;
- Capture directed information in reference relationships;
- Implement multi-model fusion and optimization of computational efficiency.

1.3 Contributions

In order, what this dissertation contributes:

(1) Leverage Heterogeneous Graph Attention Network to optimize the aggregation of information in the academic relationship networks.
(2) Utilize Spectrum based Directed graph Convolutional networks to capture academic citation network in citation relationships.
(3) Design a Layer-wise Heterogeneous Network based on multiple networks.

1.4 Organisation

Here is how this dissertation is organized. After motivating and introducing our work (this chapter), we investigate the literature to present the state-of-the-art in Section 2. We then present our great solution design in Section 3, and the result we obtained in Section 5. We then evaluate and discuss these results in Sections 6 and 7 respectively. Finally, we conclude in Section 8, highlighting limitations, and possible future work.

2 BACKGROUND

Our work relates to graph neural network, fast localized spectral filtering[Kipf and Welling 2016], heterogeneous graph neural network[Zhang et al. 2019], and attention mechanism[Vaswani 2017], which will be briefly reviewed. In Section 2.1 we explore spectrum based directed graph convolutional network, then we continue with heterogeneous graph attention network in Section 2.2. Lastly, Section 2.3 will introduce the recommendation algorithms and Section 2.3 will go into the current academic paper recommendation systems.

2.1 Spectrum based Directed Graph Convolutional Network

Spectrum based directed graph convolutional network is developed from graph neural networks and spectrum filtering. In order to facilitate understanding, we will introduce these two fields separately.

2.1.1 Graph Neural Network. The concept of Graph Neural Network(GNN) was first proposed by Gori et al. [2005] and further elaborated by Scarselli et al. [2008]. In many scenarios, data can be naturally modeled in graphical structures, such as social networks, chemical molecular structures, and so on. Based on this theory, Gori et al. [2005] designed a new type of neural network dedicated to processing data that can be represented as a graph structure, which is called graph neural network. The model is suitable for graph-focused tasks and node-focused tasks. It uses a recursive equation to update the state of a node by aggregating neighbor information. Scarselli et al. [2008] builds on its predecessor, proves the unique solution of GNN model state update equation, which ensures that the model is stable and convergent. In addition, an optimization algorithm based on Jacobi iteration is designed to reduce the complexity of the model. These efforts have made GNN models a mainstream deep learning algorithm.

2.1.2 Spectrum Filtering. Since the theory of spectrum filtering emerged from Bell LABS in the 1920s, it has been widely applied in signal processing, especially for the optimization of convolution algorithms. With the rise of neural networks pioneered by Gori et al. [2005], a Convolutional Neural Network(CNN) with fast spectral filtering has also appeared as a derivative network. Driven by the work of Lee et al. [2009], CNN is also used for image recognition, which makes the application of CNN more common. After that, Bruna et al. [2013] uses the eigenvector decomposition of Graph Laplacian in the spectrum domain, introduces spectral filtering, and extends the convolution operation to the generalized graph structure and creates the initial Graph Convolution Network(GCN). Benefiting from the contribution of Defferrard et al. [2016], who designed localized convolutional filters on graphs. The proposed technique offers linear computational complexity. And GCN obtains constant learning complexity.

Traditional spectral GCN usually only supports undirected graphs and loses directivity information when applied to directed graphs. The Directed Graph Convolutional Network (DGCN) model proposed by Tong et al. [2020] provides direct support for directed graphs, and obtains richer neighborhood information through the construction of first-order and second-order neighborhood matrices. Meanwhile, Ma et al. [2019] approximates the Laplacian operator of DGCN by using eigenvector decomposition and Chebyshev polynomials to ensure its symmetry, making the spectral method run effectively on DGCN.

2.2 Heterogeneous Graph Attention Network

Heterogeneous graph attention network is the combination of attention mechanism and heterogeneous graph neural network.

2.2.1 Attention Mechanism. Transformer, proposed by Vaswani [2017], is the first model to rely entirely on self-attention to compute its input and output representations without using sequence-aligned Recurrent Neural Network(RNN) and CNN. It proves the effectiveness of attention mechanism for global dependency modeling. Since then, Attention mechanisms are widely used in various fields of machine learning including GCN. Graph Attention Networks (GAT) proposed by Veličković et al. [2017] introduced self-attention mechanism to aggregate different neighbor nodes according to their attention weight, solves the problem of determining the importance of neighbor nodes.

2.2.2 Heterogeneous Graph Neural Network. GraphSAGE proposed by Hamilton et al. [2017] adds sampling in the updating process of neighbor nodes, so that nodes in GCN no longer need to rely on the entire neighbor information for aggregation. From there, GCN began to have the characteristics of inductive learning. However, traditional algorithms (such as GraphSAGE, GAT) are either only applicable to the homogeneous graph, or can not effectively capture information in heterogeneous graphs. The Heterogeneous Graph Neural Network(HGNN) proposed by Zhang et al. [2019] combines the Random Walk with Restart (RWR) strategy with neighbor sampling to effectively capture different types of neighbor node information. Bi-LSTM and attention mechanisms are also included to enhance coding capabilities for heterogeneous content and facilitate efficient fusion of different categories of neighbor node information. However, The ability of HGNN to model complex semantic relationships is limited. The Heterogeneous graph Attention Network (HAN) created by Wang et al. [2019] based on semantic-level attention and node-level attention successfully addresses this challenge.

2.3 Recommendation Algorithm

Neural Collaborative Filtering(NCF) recommendation algorithm which proposed by He et al. [2017] is one of the most successful technologies in recommendation system. It is inspired by Collaborative Filtering[Resnick et al. 1994] and achieves more reliable recommendation accuracy with the help of Neural Networks. On this basis, Hypergraph Contrastive Collaborative Filtering (HCCF) is proposed by Xia et al. [2022] to solve the problem of Over-Smoothing Effect, monitoring signal scarcity and noise. It uses hypergraph to capture global information effectively and contrast learning to improve the differentiation of embedded representation. As a natural algorithm suitable for modeling the relationship between nodes in recommendation system, GAT is also a widely used recommendation algorithm. In addition, reinforcement learning is also used in recommendation systems. For example, Deep Q-Network(DQN) proposed by Mnih et al. [2015] is used to maximize users' participation time and revenue. Compared with traditional methods (such as Collaborative Filtering), DQN can optimize long-term cumulative revenue and is very effective in dynamic recommendation scenarios.

With the directionality of DGCN, the Directed Acyclic Graph Convolutional Network (DA-GCN) implemented by Xiangyu et al. [2024] effectively captures the flexible path dependencies of multiple behaviors by focusing on the potential sequential relationships between different behaviors in the user-item recommendation system. For the paper citation relationship, it has obvious directivity, indicating that using DGCN modeling is reasonable.

Nowadays, most research in the field of recommendation systems focuses on the use of heterogeneous graph neural networks. For example, Jiang et al. [2023] established a Reinforced and Contrastive Heterogeneous Network Reasoning Model to improve recommendation accuracy and diversity while making it more explainable. Cai et al. [2023] uses a random walk sampling strategy and hierarchical attention aggregation mechanism to process neighbor information on HGNN, and designs an Inductive Heterogeneous Graph Neural Network. which improves the user embedding generation effect and enhances the performance of the on the cold start problem. Han et al. [2022] proposed Multi-Aggregator Time-Warping Heterogeneous Graph Neural Network for micro-video recommendation. The model makes use of Time-Warping's HGNN and serialized session modeling, which not only optimizes the micro-video recommendation effect, but also performs well in long video recommendation. Our work also involves modeling author-paper relational networks using HGNN.

2.4 Academic Recommendation

Academic pecommendation, as a hot issue in today's recommendation system, has received continuous attention from researchers. OAG-Bench[Zhang et al. 2024a], MCAP[Zhang et al. 2024b], AMinerGNN[Huai et al. 2022], Shifu2[Liu et al. 2019] and Subspace Embedding[Xie et al. 2022] use the method based on GNN, and has achieved remarkable results in academic recommendation and academic relationship mining. TAASGuo et al. [2020], Reranking[Li et al. 2019] introduce serialization modeling method to improve the accuracy and relevance of list recommendation. SearchIdea[Chavula et al. 2023] mainly uses SearchMapper and IdeaMapper to provide a novel tool to support interactive academic search. Additionally, OAG-Bench also provides a set of unified data and evaluation tool support to standardize the process of evaluation.

2.5 Summary

Although the above research has build a solid foundation for graph neural network, spectrum filtering, heterogeneous graph attention mechanism and its application in recommendation system, there are still some shortcomings. First, further progress has been made in capturing metapath based semantic relationships in heterogeneous graphs. However, it still relies on predefined meta-path weights, which makes it insufficient in scalability and adaptability to cope with complex academic relationship networks. This indicates that a mechanism for dynamically generating and optimizing metapath is needed to adapt to complex graph structures and application scenarios.

Secondly, the current research on directed graphs is mainly applied to homogeneous graphs, and the exploration of combining these techniques with heterogeneous graph neural networks is still insufficient. This provides an opportunity to design models that can capture directed information and complex semantics in heterogeneous graphs.

Finally, although many recommendation systems have achieved effective results in dealing with data sparsity and cold start problems. However, they have strict restrictions on application scenarios, such as global assumptions and predefined features. This makes their adaptability to different scenarios very limited. The introduction of directed heterograph provides a solution from a novel perspective. At the same time, in response to the increase in computing requirements, spectral filtering was introduced to alleviate this problem.

The existing shortcomings highlight the importance of our proposed approach. Our study combines spectrum-based directed graph convolution with heterogeneous graph attention mechanism to optimize the accuracy of academic recommendation system while reducing the increase of computing requirements.

Here we conclude the background and recap the concepts explored and key notions for the rest of the document.

In the next section, Section 3, we detail our design and implementation for Spectrum based Directed Graph Convolutional Network.

3 METHOD

For more accurate recommendation performance in the academic paper recommendation system, We will leverage Spectrum based Directed Graph Convolutional Network and Heterogeneous Graph Attention Network to build a new recommendation model. The reason why we chose them is they can solve two key problems in academic recommendation systems: the directionality of modeling reference relationships and the problem of relying on meta-path for heterogeneous information aggregation. These two techniques will be explained in detail in Section 3.1 and Section 3.2.

3.1 Spectrum based Directed Graph Convolutional Network

Traditional graph convolutional networks (GCNs) have difficulty in capturing the structure of directed graphs, especially in academic citation relationships, where the information flow is obviously directional. Spectrum based DGCN not only captures directional information, but also improves computational efficiency through spectral filtering. Compared to other Directed models such as Directed Acyclic Graph Convolutional Network (DA-GCN)[Thost and Chen 2021], DGCN achieves a balance between computational overhead and information retention, making it particularly suitable for dealing with citation networks. Spectrum based directed graph convolutional network is a special DGCN, which uses spectral filters to improve the convolutional efficiency without affecting the convolutional effect as much as possible. Its propagation model can be represented by Equation (1). Where X is the eigenmatrix of the node, Θ is the convolution parameter matrix that needs to be learned, Z is the result of node embedding after convolution.

$$Z = \frac{1}{2}\left(\Phi^{1/2} P \Phi^{-1/2} + \Phi^{-1/2} P^T \Phi^{1/2}\right) X \Theta \tag{1}$$

3.2 Heterogeneous Graph Attention Network

Heterogeneous graph neural networks (HGNN) mostly rely on the choice of meta paths. However, the meta-path of traditional HGNN requires manual design, resulting in low adaptability and flexibility. Heterogeneous graph attention networks (HGans) introduce a hierarchical attention mechanism that can dynamically capture and assign meta-path weights and effectively aggregate heterogeneous node interaction information. This flexibility allows it to adapt to various academic network scenarios and improve the ability to handle complex relationships between authors and papers. Heterogeneous graph attention network learns heterogeneous graph node embedding through hierarchical attention mechanisms (Node-level attention and semantic-level attention). Node-level attention can be represented by Equation (2), Equation (3), Equation (4) and Equation (5).

$$e_{ij}^{\Phi} = \mathrm{attn}_{\mathrm{node}}(h'_i, h'_j; \Phi) \tag{2}$$

$$\alpha_{ij}^{\Phi} = \frac{\exp\left(\sigma(a_{\Phi}^{\top} \cdot [h_i' \| h_j'])\right)}{\sum_{k \in N_i^{\Phi}} \exp\left(\sigma(a_{\Phi}^{\top} \cdot [h_i' \| h_k'])\right)} \tag{3}$$

$$z_i^{\Phi} = \sigma\left(\sum_{j \in N_i^{\Phi}} \alpha_{ij}^{\Phi} \cdot h_j'\right) \tag{4}$$

$$z_i^{\Phi} = \|_{k=1}^{K} \sigma\left(\sum_{j \in N_i^{\Phi}} \alpha_{ij}^{\Phi,k} \cdot h_j'^{k}\right) \tag{5}$$

4 LAYER-WISE HETEROGENEOUS NETWORK

To achieve more accurate and comprehensive academic recommendation, we proposed a Layer-wise Heterogeneous Network. This method integrates spectrum-based directed graph Convolutional networks (DGCN) and heterogeneous graph attention networks (HGAN) to complement their strengths. The first layer focuses on the paper nodes, using DGCN to model the directionality of citation relationships to ensure that the directionality of the citation flow is effectively captured. The second layer uses HGAN for global aggregation. HGAN's node-level and semantic-level attention mechanisms can dynamically capture meta paths and assign weights, and aggregate information from different node types. This allows the network to handle complex academic interactions, such as author collaboration, papers from the same conference.

4.1 Summary

This chapter has detailed our system implementation. In particular, we have divided the processes into the (Section 3.1), the front-end (Section 3.2). Lastly, we will merge these two networks to achieve joint academic paper recommendation.

In the next chapter, Section 5, we present the expected findings of our research.

5 RESULTS

5.1 Results about B

5.2 Results about A

5.3 Summary

6 ANALYSIS

6.1 Feasibility and Effectiveness Analysis

Our model integrates DGCN and HGAN to provide solutions to key challenges in academic recommendation systems, such as data sparsity and lack of referential orientation modeling. The directed property of DGCN enables the model to capture the directional information inherent in the citation network and avoid the wrong influence of low-quality papers through undirected information propagation. At the same time, HGAN uses the attention mechanism to dynamically assign meta-path weights, ensuring that heterogeneous interaction information between nodes (such as authors, papers) is effectively aggregated. The combined structure will provide new ideas to overcome the limitations of traditional models to apply to complex academic networks. The validity of the model will be verified by the following evaluation indicators, which evaluate the recommendation performance in terms of relevance (Recall), sort quality (MRR), and relevance-place tradeoff (NDCG).

6.2 Evaluation Method Analysis

In this section, we evaluate the system developed in Section 3 and the results described in Section 5 with three criteria, Recall(Section 6.2.1), MRR(Section 6.2.2) and NDCG(Section 6.2.3). Recall, Mean Reciprocal Rank(MRR) and Normalized Discounted Cumulative Gain(NDCG) are widely recognized evaluation criteria in the research of recommendation systems. As they can capture different aspects of model performance, they are necessary parts to evaluate our academic recommendation systems. By using these criteria to compare our models to current state-of-the-art benchmarks, we ensure that the performance of academic recommendation tasks is fully assessed.

6.2.1 Recall. Recall considers the percentage of papers that have been accurately recommended. This metric measures the model's accuracy in finding papers that align with the user's interests or queries, and is a direct reflection of the model's ability to mitigate data sparsity by identifying as many relevant papers as possible. It can usually be represented as Equation (6), where $RelevantItems$ is the collection of Items that the user is actually interested in, and $Recommendeditems@K$ is the first K items in the recommended list.

$$\text{Recall@K} = \frac{|\text{Relevant Items} \cap \text{Recommended Items@}K|}{|\text{Relevant Items}|} \tag{6}$$

6.2.2 Mean Reciprocal Rank. MRR measures the average ranking of the first positive sample. Users often expect highly relevant papers to appear at the top of the recommendation list, and MRR emphasizes the model's ability to prioritize these papers, aiming to reduce the cost of finding valuable papers for users. It can be expressed as Equation (7), where $|U|$ is the total number of users and Rank_u is the rank of the first correct item for the u user.

$$\text{MRR} = \frac{1}{|U|}\sum_{u=1}^{|U|}\frac{1}{\text{Rank}_u} \tag{7}$$

6.2.3 Normalized Discounted Cumulative Gain. The NDCG takes into account relevance and location when measuring recommendations. The criterion balances relevance and ranking order, is more comprehensive than Recall or MRR alone, and reflects users' preference for relevant papers at the top of the recommendation list. It can be expressed as Equations (8) to (10), where rel_i is the relevance score of the item at position i, K is the length of the recommended list, and *IDCG@K* is the *DCG* value of the recommended list in optimal order.

$$\text{DCG@K} = \sum_{i=1}^{K}\frac{2^{\text{rel}_i}-1}{\log_2(i+1)} \tag{8}$$

$$\text{IDCG@K} = \sum_{i=1}^{|REL|}\frac{2^{\text{rel}_i}-1}{\log_2(i+1)} \tag{9}$$

$$\text{NDCG@K} = \frac{\text{DCG@K}}{\text{IDCG@K}} \tag{10}$$

6.3 Summary

In this section, we analyze the feasibility and validity of our model and introduce the evaluation methods that will be used to evaluate the model. The evalution results on Recall, MRR and NDCG(Sections 6.2.1 to 6.2.3) will be used to verify whether the model is effective in academic recommendation task.

This chapter concludes the work carried out during the project. In the next chapter, Section 7, we discuss our findings and their implications.

7 DISCUSSION

This section provides a discussion of derived problems about the methodology, results and analysis presented in Sections 3, 5 and 6.

7.1 Professional Issue

7.1.1 Has the recommendation algorithm been thoroughly evaluated from multiple perspectives? We will use multiple evaluation indicators such as Recall, NDCG, etc., to evaluate the model performance based on multiple data sets to ensure that the evaluation is comprehensive.

7.1.2 Does the recommendation algorithm use reliable enough technology to meet academic standards? Our model will use the most effective recent research results, such as Directed Graph Convolutional Network, Heterogeneous Graph Attention Network, etc., to ensure that the techniques used are advanced.

7.2 Legal Issue

7.2.1 Is the source of academic paper data legitimate? Our dataset comes from open source datasets such as AMiner. The data collection process is legal and compliant.

7.2.2 Is user privacy in the data set properly protected? All privacy-related information in the data set, such as names, interaction records, etc., have been desensitized, and digital serial numbers have been used to replace private information.

7.3 Ethical Issue

7.3.1 Does the system treat different fields of research fairly? The recommendation system has no field label, and papers in different fields will be treated equally.

7.3.2 Does the system's recommendation result take into account the diverse needs of users, rather than over-recommendation in a single direction? The algorithm used by the system includes HGNN, which has a significant effect on cross-domain recommendation and improves the diversity of recommendation effects.

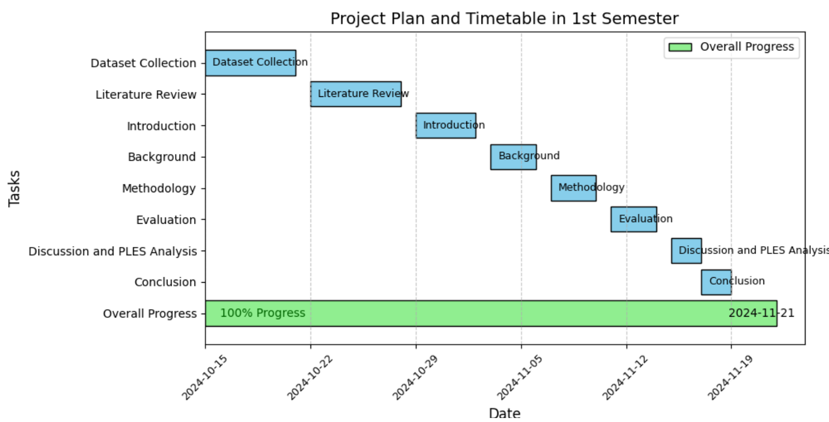
7.4 Social Issue

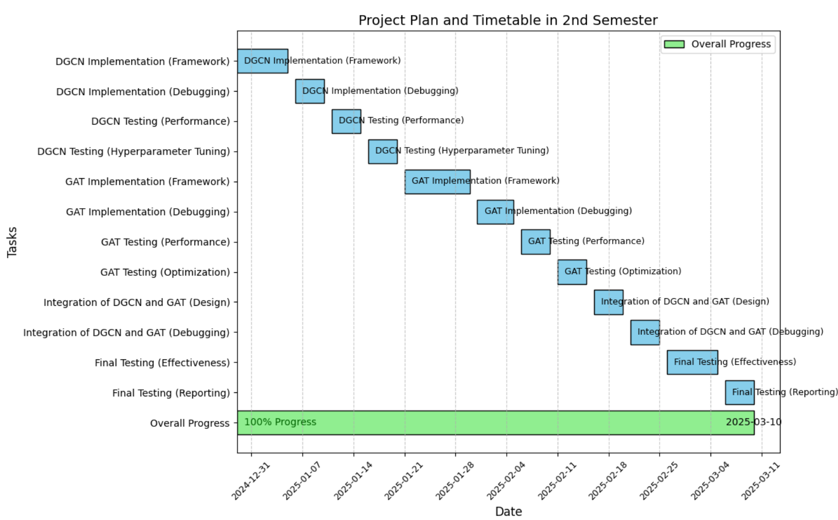
7.4.1 Will the system have a tendency to recommend papers from well-known institutions or developed regions, resulting in an imbalance in resource allocation? The model does not take regional and institutional labels into account, and only uses the interaction between author and paper to establish the relationship network, so it does not lead to uneven resource allocation.

7.4.2 Will the system help lower academic barriers and make cutting-edge research accessible to more people? Our recommendation system aims to provide more personalized paper recommendations. For beginners or cross-disciplines, it will help to recommend articles that are more suitable for getting started. And according to the user's ability to improve, continue to recommend more in-depth academic papers.

7.5 Project Plan and Timetable

In order to allocate time reasonably, plan the phased goals of the project to gradually achieve the final effect. We made a project plan and marked the timetable.





7.6 Risk Analysis

The following table shows information about possible problems and what to do about them.

Risk Name	Possibility of Occurrence	Implication	Coping Strategy
Technical Challenge	H	H	Consult with supervisor
Software Bugs	H	M	Switch the software version
Insufficient Dataset	L	M	Find alternative datasets
Ill	L	M	Make redundant timetable

7.7 Safe Core and Challenging Activities

In order to meet the minimum requirements for academic paper recommendations, Our recommendation system can be implemented with at least one of the Spectrum based Directed Graph Convolutional Network and Heterogeneous Graph Attention Network. The implementation of a single network is simpler, but it will also improve the shortcomings of the existing model recommended in academic papers.

In our recommendation system, the most challenging goal is to fuse the Spectrum based Directed Graph Convolutional Network and Heterogeneous Graph Attention Network. The appropriate combination method can dramatically improve the accuracy of academic paper recommendation and play a joint recommendation effect. But its complexity and uncertainty are also a challenge.

8 CONCLUSION

8.1 Motivation and Goals

8.2 Contributions

8.3 Limitations and Future Work

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