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

In the existing academic recommendation system, how to effectively model the citations between papers is still a challenge, especially in capturing the citation relation directionality and semantic asymmetry. The traditional heterogeneous graph model often simplifies citations into undirected links and ignores the semantic differences between citations and citations in academic communication. However, the existing directed graph methods generally rely on unidirectional aggregation strategy, which is difficult to describe the actual flow pattern of influence flexibly. To solve the above problems, we propose a new Citation Neural Network model, Citation Neural Network (CitationNN), which introduces bidirectional asymmetric heterogeneous directed edges to conduct bidirectional semantic modeling of citation behavior, and uses double convolution kernel to process the semantic information of "cite" and "be cited" respectively. Achieve dynamic selection and characterization of the underlying academic intent in the reference path. At the same time, the structure of the model is simple, easy to integrate with user-paper interaction diagram, and has good scalability and generalization. A large number of experimental results show that CitationNN is significantly better than the existing representative models on several recommendation indicators, showing strong recommendation ability and academic semantic understanding potential. Model code and data is open from: https://github.com/juyujing/CitationNN.

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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. 2011a] 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 $\rightarrow$ Paper $\rightarrow$ Venue). It can also represent the cooperative relationship between authors(Author $\rightarrow$ Paper $\rightarrow$ 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. 2019c] 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 series of problems raised by this omission will be heavily considered.

At present, the directionality of directed reference relationships is often neglected in the academic citation network. Although some studies have introduced a Directed Graph Convolutional Network [Tong et al. 2020b] to capture this directed information flow, which in theory can better model the unidirectivity of references, the actual results are not satisfactory. The main difficulty is how to accurately handle the direction of information flow and suppress noise and misdirection while preserving the reference semantics. In other words, although DGCN provides a structured means for modeling directionality, in the highly heterogeneous and structural-complex scenario of academic network, its modeling ability for directionality in reference relationships is still insufficient, and it cannot effectively avoid confusion and misdirection and missing crucial information during the transmission of reference information.

The problems of structural modeling deficiency and semantic path selection challenges in every academic recommendation system will be alleviated by our work. Especially for the flow of information in the directed mode, the correct capture of directed reference relationships will significantly improve the recommendation accuracy.

1.1 Motivation

Two main dilemmas persist in the current academic recommendation system in citation network modeling: One modeling method constructs the whole academic network as a heterogeneous graph (as illustrated in Figure 1) with heterogeneous nodes, homogeneous and undirected edges, models different entities such as papers, users and topics as heterogeneous nodes, and unoriented homogeneous edges are unified among interactions, citations and co-authors. In such a structure, the citation relationship is reduced to a common link relationship, which cannot reflect the unequal semantic roles of citation and citation in information transmission. The design focus is more on describing the overall structure of the academic network and the interactive behavior between users and papers, ignoring the internal logic and academic inheritance path between papers.

The other kind of method constructs the directed graph structure (as illustrated in Figure 2) specifically for reference relation, and uses the digraph neural network to model it separately. Although such methods can reflect certain directionality, they usually only use one-way edges for aggregation, and the designer needs to specify the direction of information flow (such as always along the reference direction or always along the referenced direction). As a result, the model cannot flexibly capture semantic differences and direction dependence in the real context of reference, thus missing key information and affecting the accuracy of recommendation.

1.2 Aim and Objectives

We propose a Citation Neural Network (CitationNN), a graph neural network based on node homogeneity and edge heterotopic directed structure. The core design of the model is as follows: for each pair of paper nodes with citation relationship, two heterogenous edges in opposite directions are established at the same time, respectively representing two semantically explicit

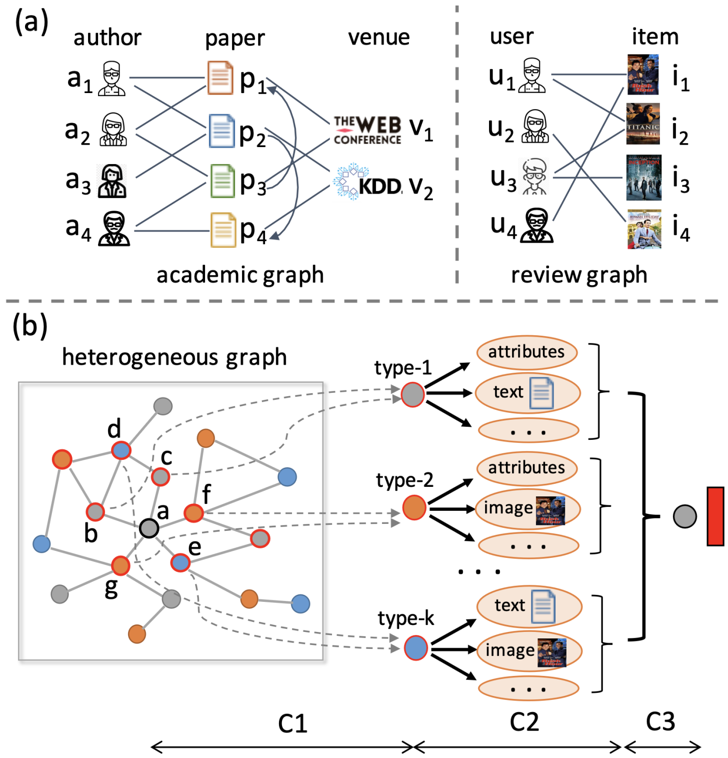

Fig. 1. (a) Heterogeneous Graph examples: an academic graph and a review graph. (b) Heterogeneous Graph structure: C1- sampling heterogeneous neighbors (for node a in this case, node colors denote different types); C2 - encoding heterogeneous contents; C3 - aggregating heterogeneous neighbors. Adapted from Zhang et al. [2019].

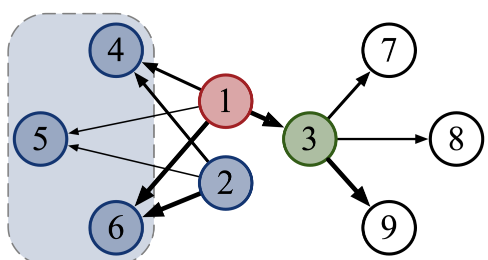

Fig. 2. A simple weighted directed graph example. Adapted from Tong et al. [2020a].

behaviors of "cite" and "cited by". These two kinds of edges share the node representation during training, but the information is aggregated through two different sets of convolution parameters. The model does not rely on external annotations or explicit path design, but through end-to-end learning, automatically determines whether the "cite" or "cited by" edge should be used in each information transmission for semantically optimal aggregation.

This design stems from our reunderstanding of citation behavior: a paper in the process of being recommended may be associated with the topic because it actively cites some core literature, or it may demonstrate domain influence because it is frequently cited by others. They represent very different semantics, and modeling with the same edge or shared parameters will not capture this detail. Therefore, CitationNN enables the model to have structural semantic resolution through "heterogeneous bilateral design + double convolution kernel", and allows the information aggregation strategy to be dynamically adjusted according to the node context during training, so as to preserve the semantic structure and information flow direction in the citation network to the maximum extent.

We analyze the flow pattern of information in this bidirectional heterogeneous structure. Although from the perspective of graph structure, the direction of citation and the direction of being cited are two sides set symmetrically, in the actual academic context, the influence tends to concentrate on high-quality papers. CitationNN does not assume a certain side as the dominant side a priori, but allows the model to independently learn which side the influence spreads with through loss guidance in training, and then capture the potential structural rules in academic citations. In practice, we observe that the model tends to establish a stable aggregation mechanism in the "cite" direction (i.e. the inflow direction of the cite edge), which is consistent with the knowledge accumulation logic in the real academic context, indicating that the structure has good semantic correspondence and explanatory power.

The structure of CitationNN is simple and modular, and it is easy to combine with the existing user-paper heterogeneous graph neural network model to form a joint modeling system. When combined, CitationNN can be used as an independent module to independently process the citation-to-paper citation structure, produce a paper representation with directional semantics, and fuse it with the user-to-paper representation in the heterogeneous graph. Since CitationNN adopts a nodal homogenous design and does not introduce new node types or extend the original heterogeneous graph structure, it will not interfere with the existing semantic modeling process in the heterogeneous graph neural network, nor will it destroy the representation learning space of user-paper interaction graph, so as to ensure the stability and effectiveness of the original system in the recommendation task. On the contrary, the semantic information of academic citations introduced by CitationNN can supplement the missing context-paper structure in the heterogeneous graph, and further improve the model's ability to identify potential academic values and the extension of the scope of recommendation.

1.3 Contributions

In this paper, the reference network modeling and semantic extension of the recommendation system are studied. From the perspective of the modeling method of the reference edge class, the exploration of information transmission structure, and the modular integration mechanism, a graph neural network system with the ability of semantic differentiation and practical integration is constructed to make up for the gaps in the processing of the semantic structure of the reference in the existing academic recommendation methods.

In order, what this dissertation contributes:

(1) In this paper, a bi-directional heterogeneous edge modeling framework is proposed. For each pair of paper nodes with a citation relationship, two heterogeneous edges are established in opposite directions, respectively representing the academic behavior of "cite" and "be cited", and the explicit splitting of the citation semantics is realized from the level of edge class. This design breaks through the simplified assumption of traditional graph neural networks that reference is a single edge class or undirected edge, and enables the model to perceive and learn the semantic asymmetry of the role in academic behavior at the structural level.

(2) A dual convolution kernel aggregation mechanism based on heterogeneous edges is designed. Independent parameter Spaces are set for the "cite" and "be cited" edge classes respectively. Through end-to-end training, the model can independently select the edge classes and convolution cores used in information dissemination according to the node context and structural context. This mechanism eliminates the artificial assumption about the direction of information flow and endows the model with the ability to flexibly invoke semantic channels in different scenarios, so as to realize learnable modeling of semantic and direction selection in reference structure.

(3) A citation modeling module is designed that can be seamlessly integrated with existing heterogeneous graph neural networks (such as recommendation system based on user-paper interaction). CitationNN only introduces heterogeneous directed edges inside the paper nodes, without adding node types, changing the original heterogeneous graph structure, or affecting the feature embedding structure of heterogeneous nodes. The reference semantic representation is introduced to ensure the stability of the recommendation system. The integrated system can learn from the dual context of user interaction and citation network at the same time, and strengthen the comprehensive judgment ability of the model to the paper value and the extension of the scope of cross-domain recommendation.

This series of design focuses on the semantic modeling of academic citations, and further fills the structural gap of the existing recommendation system in semantic representation and logical processing of citations.

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 4. We then evaluate and discuss these results in Sections 5 and 6 respectively. Finally, we conclude in Section 7, 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 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 the 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. [2020b] 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. [2019c] 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 [Goldberg et al. 1992] 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 (DAGCN) 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 recommendation, 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 have achieved remarkable results in academic recommendation and academic relationship mining. TAASGuo et al. [2020], Reranking[Li et al. 2019] introduce serialization modeling 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 built 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[Sun et al. 2011b] 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 selecting 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 several recommendation systems have achieved remarkable results in dealing with heterogeneous data structures, these methods often place strict limitations on application scenarios, such as relying on global consistency assumptions, relying on predefined feature templates, and lacking adaptive capabilities for dynamic network structures. More importantly, when these methods are applied to recommendation scenarios with complex structure and diverse semantic levels, such as academic networks, they show very poor model integration ability, which is difficult to be used together with other recommendation modules, and it is easy to interfere with the effect of the original model in the fusion process, resulting in the overall performance of the system. The Citation Neural Network proposed by us adopts the structural design of node homogeneity and edge heterogeneity, and has the characteristics of high modularity, clear semantics and independent convolutional kernel. It can be embedded into various recommendation systems as an independent structural module, providing the capability of citation semantic modeling without affecting the original recommendation framework. It significantly improves the scalability and semantic completeness of the recommendation system in complex and heterogeneous scenarios.

The limitations revealed by the existing work have prompted us to rethink the way we model semantics and directionality in heterogeneous graphs. Faced with the increasingly complex academic network structure, it is difficult for the graph neural architecture that relies solely on predefined metapath and one-way information propagation to cover various scenarios in citation semantics. Especially in the behavior of quoting, the roles of "cite" and "be cited" are not equal in the structure, but they are often simplified into symmetric or undirected relations, which weakens or even misplaces the semantics of information in the process of transmission. In addition, existing heterogeneous graph models generally take node types as the basis for semantic division, ignoring the semantic differences and direction constraints carried by edge classes themselves, and it is difficult to effectively capture the internal knowledge flow and influence diffusion mode when facing highly structured academic data.

"Metapath", as the core semantic component in heterogeneous graphs, usually refers to a directed correlation sequence composed of specific types of nodes and edges, such as author-paper-venue - paper-author, which can be used to describe different semantics such as cooperative relationship, topic diffusion, and academic inheritance. However, most of the existing methods rely on manually predefined meta-path sets and set their weights, which lack structural flexibility and semantic adaptability for academic networks with rapid semantic changes and complex structural relationships.

To solve this problem, we did not directly screen and optimize the meta-path set explicitly. Instead, we constructed a reference network composed of node homogeneity and edge heterogeneity directed from the semantic nature of reference relations, modeled "cite" and "be cited" as two structurally distinct semantic edges, and designed an independent convolution kernel for them. This design can be regarded as an indirect reconstruction of the meta-path modeling approach: reference-related semantic paths no longer rely on manually defined node type sequences, but are formed by dynamic combinations of heterogeneous directional edges in the model. The information transfer direction and semantic selection are not set in advance, but the model chooses the appropriate edge class and convolution kernel for aggregation during the training process. This modeling approach provides an "implicit meta-path" with dynamic assembly and learnable semantics at the structural level, which can be adapted to more diverse academic network scenarios and make up for the shortcomings of existing heterogeneous graph models in semantic construction and path flexibility.

In addition, our model will adopt the structural design of node homogeneity and edge heterogeneity, carry out independent modeling of different semantics with convolution check, and realize information aggregation in a modular way, with the characteristics of clear semantic logic and clear structural boundary. This enables the model to be flexibly embedded into various heterogeneous recommendation systems as an independent submodule, providing additional reference semantic modeling capabilities without changing the original framework structure and node type design. In the scenario where the recommendation system is faced with structural heterogeneity and semantic fragmentation, this model can stably expand the semantic representation range without interfering with the representation learning process of other modules, and improve the generalization ability and scalability of the whole system under multi-scenario conditions.

This structure design lays a double foundation of semantic and system layers for the construction and application of the subsequent model.

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 Citation Neural Network.

3 METHOD

In this section, we present **Citation Neural Network (CitationNN)**, a graph-based framework that models both user-item interactions and citation relationships between academic papers. CitationNN consists of two major components: (1) a user-item interaction network and (2) a directed citation-aware convolutional network. The following sections formally define the mathematical foundations of the model and describe all equations in detail.

3.1 Overview

CitationNN operates on a heterogeneous graph G consisting of two subgraphs:

1. **User-Item Bipartite Heterogeneous Graph**: A bipartite graph $G_{ui} = (U, I, E_{ui})$, where U is the set of users, I is the set of academic papers, and E_{ui} represents observed interactions (e.g., clicks, downloads). 2. **Directed Citation Graph**: A directed graph $G_c = (I, E_c)$, where E_c consists of paired directed heterogeneous edges representing citation relationships between papers.

Given G, the goal is to learn low-dimensional embeddings $\mathbf{h}_u$ for each user $u \in U$ and $\mathbf{h}_i$ for each paper $i \in I$, which preserve both collaborative filtering and citation-based information.

The overall model structure is illustrated in Figure 3.

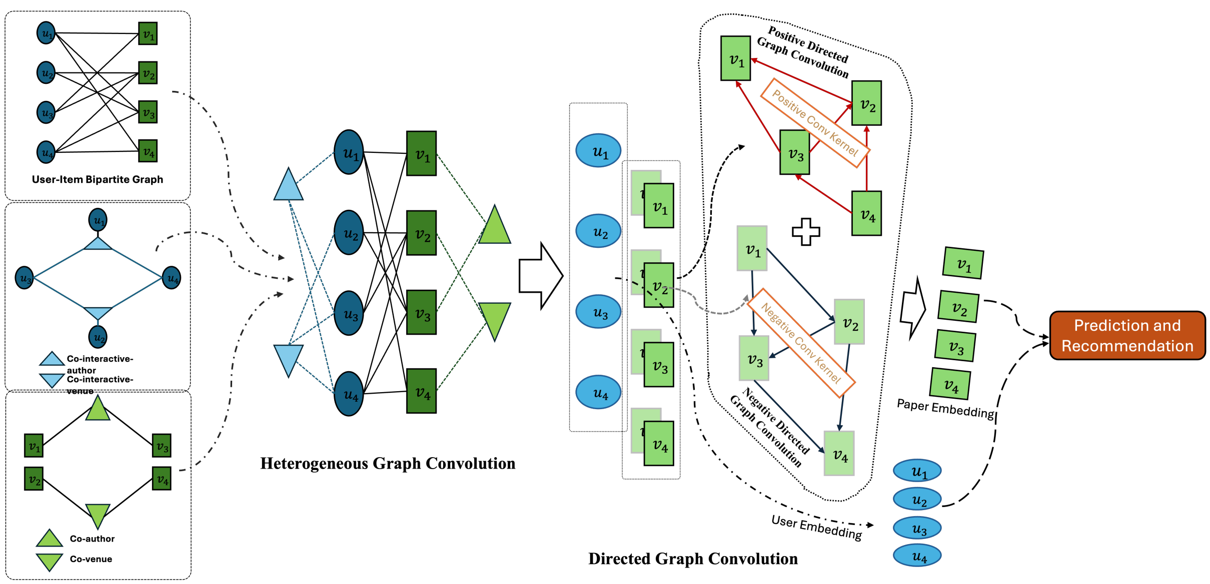

Fig. 3. Citation Neural Network Model Framework.

3.2 User-Item Heterogeneous Graph Convolution

To model collaborative filtering signals, we apply graph convolution on the user-item bipartite graph. The embeddings are updated using a message-passing mechanism:

$$\mathbf{h}_u^{(l+1)} = \sum_{i \in N(u)} \frac{1}{\sqrt{|N(u)||N(i)|}} \mathbf{h}_i^{(l)} \tag{1}$$

$$\mathbf{h}_i^{(l+1)} = \sum_{u \in N(i)} \frac{1}{\sqrt{|N(i)||N(u)|}} \mathbf{h}_u^{(l)} \tag{2}$$

where: - $N(u)$ and $N(i)$ denote the neighboring items for user u and the neighboring users for item i, respectively. - $\mathbf{h}_u^{(l)}$ and $\mathbf{h}_i^{(l)}$ represent the embeddings of user u and item i at layer l.

This process allows information propagation between users and items, refining their embeddings based on observed interactions.

3.3 Directed Citation Graph Convolution

The directed citation graph processes citation relationships through two separate graph convolution kernels. One kernel captures the forward citation relationships where a paper cites another, while the other captures backward citation relationships where a paper is cited by another.

For a given paper i, the embedding updates follow two distinct aggregation mechanisms:

$$\mathbf{h}_{i,\text{cites}}^{(l+1)} = \sum_{j \in N_{\text{cites}}(i)} \frac{1}{\sqrt{|N_{\text{cites}}(i)||N_{\text{cites}}(j)|}} \mathbf{h}_j^{(l)} \tag{3}$$

where: - $N_{\text{cites}}(i)$ represents the set of papers cited by i. - $\mathbf{h}_j^{(l)}$ is the embedding of paper j at layer l. - The normalization factor accounts for the degree of nodes to prevent bias in aggregation.

Similarly, for the reverse citation relationship where i is cited by other papers, the embedding is updated as:

$$\mathbf{h}_{i,\text{cited by}}^{(l+1)} = \sum_{j \in N_{\text{cited by}}(i)} \frac{1}{\sqrt{|N_{\text{cited by}}(i)||N_{\text{cited by}}(j)|}} \mathbf{h}_j^{(l)} \tag{4}$$

where: - $N_{\text{cited by}}(i)$ represents the set of papers that cite i. - The normalization factor ensures stable information propagation across different citation patterns.

After obtaining both forward and backward citation embeddings, they are concatenated and transformed through a fully connected layer:

$$\mathbf{h}_{i,\text{combined}}^{(l+1)} = \mathbf{W}[\mathbf{h}_{i,\text{cites}}^{(l+1)}, \mathbf{h}_{i,\text{cited by}}^{(l+1)}] \tag{5}$$

where: - $\mathbf{W}$ is a learnable transformation matrix. - The concatenation operation aggregates information from both citation directions.

A residual connection is introduced to integrate the original embedding with the transformed citation-aware embedding:

$$\mathbf{h}_i^{(l+1)} = (1-\alpha)\mathbf{h}_{i,\text{combined}}^{(l+1)} + \alpha \mathbf{h}_i^{(l)} \tag{6}$$

where: - α is a learnable parameter that controls the balance between the original and updated embeddings.

This mechanism ensures that citation-aware information is effectively incorporated while preserving the integrity of the original paper embeddings.

3.4 Preference Prediction

To compute the preference score of user u for item i, we use the inner product:

$$\hat{y}_{ui} = \mathbf{h}_u^\top \mathbf{h}_i \tag{7}$$

where $\hat{y}_{ui}$ represents the predicted relevance score.

3.5 Computation Framework

The CitationNN model can be expressed in matrix form. Define $R \in \mathbb{R}^{|U|\times|I|}$ as the user-item interaction matrix, $T \in \mathbb{R}^{|U|\times|U|}$ as the user-user relation matrix, and $S \in \mathbb{R}^{|I|\times|I|}$ as the citation-based item-item relation matrix.

We construct the full adjacency matrix:

$$A = \begin{bmatrix} T & R \\ R^\top & S \end{bmatrix} \tag{8}$$

Let $E^{(0)} \in \mathbb{R}^{(|U|+|I|)\times d}$ be the initial embedding matrix, where d is the embedding size. The propagation rule for CitationNN is given by:

$$E^{(l+1)} = D^{-1/2} A D^{-1/2} E^{(l)} \tag{9}$$

where D is the degree matrix of A, and $D^{-1/2}AD^{-1/2}$ represents the symmetric normalization.

The final embedding is obtained as:

$$E = E^{(0)} + E^{(1)} \tag{10}$$

where $E^{(1)}$ captures higher-order interactions in the graph.

3.6 Optimization Objective

The model is trained using the Bayesian Personalized Ranking (BPR) loss:

$$\mathcal{L} = -\sum_{(u,i,j)\in\mathcal{D}} \ln \sigma(\hat{y}_{ui} - \hat{y}_{uj}) + \lambda||\Theta||^2 \tag{11}$$

where: - $\sigma(x)$ is the sigmoid function. - (u, i, j) represents a training triplet where i is a positive item, and j is a randomly sampled negative item. - $\lambda||\Theta||^2$ is an L_2 regularization term.

3.7 Summary

This chapter has detailed our system implementation. In particular, we have divided the processes into the User-Item Heterogeneous Graph Convolution (Section 3.2), and the Directed Citation Graph Convolution (Section 3.3). Lastly, we will merge these two networks to achieve joint academic paper recommendation.

In the next chapter, Section 4, we present the expected findings of our research.

4 RESULTS

In this section, we will show the data sets used, the baselines selected, and the results of our model against each baseline on different data sets and various metrics.

4.1 Datasets

On the premise of ensuring data anonymity and protecting user privacy, we selected two publicly available datasets from the real world, CiteULike and DBLP[Wang et al. 2013], to evaluate the Citation model.

- **CiteULike**[1] is collected from CiteULike and Google Scholar, which allows users to create their own collections of articles. CiteULike-a and CiteULike-t are widely used for academic paper (citation) recommendations. We select CiteULike-a in our experiments and use the same 10-core setting to ensure data quality.
- **DBLP**[2] originates from the open data platform of AMiner, curated by researchers at AMiner. It encompasses 1,632,441 academic papers, each furnished with title, abstract, authors, publication year, and venue information. We filtered out papers lacking citation data or with fewer than 10 citations. From the remaining dataset, we selected 85,637 papers and their 232,628 cited references. Our objective is to perform citation recommendations for the former group, aiming to validate the effectiveness of CitationNN on this extensive dataset.

4.2 Baselines

We select traditional models in various fields and state-of-the-art baselines for performance comparison.

- BPR-MF[Rendle et al. 2012] is a Bayesian personalized ranking method that uses the LearnBPR algorithm for implicit feedback. It optimizes the maximum posterior estimator through stochastic gradient descent and bootstrap sampling.
- NeuMF[He et al. 2017] combines Matrix Factorization (MF) with deep neural networks to leverage collaborative filtering on implicit feedback. It allows separate embeddings for GMF and MLP, and their outputs are combined through the concatenation of their last hidden layers.
- NCL[Lin et al. 2022]] introduces a neighbor-enriched contrastive learning framework that employs two types of contrastive learning: one based on structural neighbors and the other based on semantic neighbors. By incorporating a neighbor from both the graph structure and the semantic space, it aims to capture more potentially relevant information between users and items.

[1]https://github.com/js05212/citeulike-a

[2]https://open.aminer.cn/article?id=655db2202ab17a072284bc0c

- UltraGCN[Mao et al. 2021] is an optimized graph convolutional network that avoids the use of infinite layers of message passing and explicit message passing. Instead, it accomplishes efficient recommendation tasks by flexibly adjusting the importance of relationships.
- NGCF[Wang et al. 2019b] is a recommendation framework that utilizes graph neural networks to improve user and item representations by incorporating the user-item graph structure in the process of learning embedding.
- •LightGCN[He et al. 2020] incorporates the user-item graph structure using graph neural networks. It improves user and item representations by capturing high-order connectivity and injecting collaborative signals.
- ApeGNN[Zhang et al. 2023] addresses the limitations of existing GNNs in capturing diverse local patterns in recommendation systems by enabling each node to determine its diffusion weights based on the local structure adaptively.
- MCAP[Zhang et al. 2025] is a state-of-the-art academic recommendation model that integrates low-pass propagation and matrix completion into a relation-aware heterogeneous GNN framework. It constructs user-user and item-item graphs based on co-authorship, co-venue, and content similarity, and enhances learning through fine-grained relation selection using attention mechanisms and language models.

4.3 Performatnce Comparison

To verify the performance of CitationNN, we performed comparative experiments with current state-of-the-art models. We first give the overall comparison results, and analyze CitationNN with different types of frontier models in detail.

4.3.1 Overall Comparison. Table 1 and Table 2 show the comparison results of CitationNN with various representative models on CiteULike and DBLP datasets, respectively. We underline the next best results in each metric, underline the best results in bold, and calculate the relative performance improvement of CitationNN compared to the next best model. All results are the average of three experiments under fixed random seeds to ensure the stability and reproducibility of the model performance.

- CitationNN comprehensively outperforms MCAP on CiteULike and DBLP datasets. CitationNN significantly outperformed MCAP on all evaluation measures and achieved up to 19.2% improvement on several key measures. This fully demonstrates the superiority of CitationNN in the task of academic paper recommendation.
- CitationNN uses a more advanced relational modeling approach that combines user-paper and paper-paper heterogeneous graph information to further improve the quality of recommendations. Although MCAP is a significant improvement over traditional methods, CitationNN still achieves higher performance on all datasets, further demonstrating its superior recommendation capabilities.

Dataset	Metrics	BPR-MF	NeuMF	NCL	UltraGCN	NGCF	LightGCN	ApeGNN	MCAP	**CitationNN**	%Improv.
CiteULike	Recall@5	1.30	0.25	1.39	1.08	1.24	1.31	1.24	1.51	**1.81**	19.2%
	Recall@10	2.29	0.59	2.41	1.95	2.11	2.21	2.08	2.65	**2.96**	11.9%
	Recall@20	3.89	1.09	4.13	3.57	3.76	3.90	4.13	4.65	**5.21**	12.1%
	NDCG@5	1.08	0.26	1.16	0.83	1.03	1.15	1.05	1.23	**1.45**	17.5%
	NDCG@10	1.50	0.38	1.59	1.20	1.38	1.53	1.41	1.72	**1.95**	13.2%
	NDCG@20	2.04	0.55	2.17	1.75	1.94	2.10	2.10	2.43	**2.77**	13.7%
	HR@5	3.13	0.94	3.01	2.40	2.95	3.19	2.86	3.66	**4.15**	13.3%
	HR@10	5.44	1.84	5.57	4.27	4.95	5.31	4.92	6.38	**6.93**	8.5%
	HR@20	9.22	3.17	9.35	8.04	8.48	9.17	9.66	10.63	**11.62**	9.2%
DBLP	Recall@5	9.91	11.19	10.73	7.60	6.91	9.74	12.79	14.17	**x**	x%
	Recall@10	15.12	17.14	16.75	12.31	10.90	15.27	19.78	21.79	**x**	x%
	Recall@20	21.91	24.44	24.98	18.68	16.48	22.71	28.34	31.11	**x**	x%
	NDCG@5	7.99	8.92	8.53	5.90	5.51	7.77	10.08	11.22	**x**	x%
	NDCG@10	10.06	11.09	10.91	7.76	7.09	9.96	12.86	14.24	**x**	x%
	NDCG@20	12.18	13.38	13.48	9.75	8.83	12.28	15.54	17.17	**x**	x%
	HR@5	18.79	20.56	20.35	14.84	13.58	18.53	23.56	25.86	**x**	x%
	HR@10	27.35	30.25	30.04	22.94	20.62	27.77	34.37	37.43	**x**	x%
	HR@20	37.59	40.83	42.14	33.08	29.64	38.92	46.21	50.05	**x**	x%

Table 1. Comparison of CitationNN and various baselines on multiple datasets

4.3.2 Compare with different types of frontier models. We compare CitationNN with three mainstream recommendation models: MF-based (matrix decomposition), GNN-based (graph neural network), and Knowledge-Aware (Knowledge Enhancement).

Comparison with matrix decomposition model. Table 1 shows that on CiteULike and DBLP datasets, the higher-order graph neural network model (NGCF, LightGCN, ApeGNN) is generally superior to the traditional matrix decomposition methods (BPR-MF, NeuMF). However, it is notable that on the CiteULike dataset, NCF still maintains competitiveness, and even outperforms most GNN models. In contrast, CitationNN significantly outperforms matrix decomposition models on all metrics. This shows that CitationNN combines graph information to build richer context information on the basis of matrix decomposition, thus significantly improving the recommendation effect.

Comparison with graph neural network (GNN) model. In our experiments, CitationNN demonstrated stronger recommendation capabilities than existing GNN models, including the state-of-the-art MCAP. CitationNN has achieved significant improvement in various evaluation indicators. Its core advantage lies in building topological structures among papers directly based on the citation network, so that the model can learn the citation relationships among papers more accurately, and thus improve the accuracy of recommendation. Compared with MCAP, which only uses collaborative signals to model the interaction between users and papers, CitationNN can mine semantic associations between papers from the citation network and strengthen the construction of paper representation. The experimental results show that

CitationNN achieves better results in academic recommendation tasks by introducing citation network structure, which further proves the importance of using paper citation information under the framework of GNN.

Comparison with knowledge enhancement model. In the field of heterogeneous graph neural network recommendation, Knowledge-Aware method is an important research direction. We did a detailed comparison with KGCN[Wang et al. 2019d], KGAT[Wang et al. 2019a] and Simple-HGN[Lv et al. 2021]. As shown in Table 2, the experimental results show that CitationNN outperforms the existing knowledge enhancement recommendations on all datasets. Compared with KGCN, KGAT and Simp-HGN, CitationNN can construct graph networks using only author and citation information, and relies on efficient relationship modeling mechanism to achieve better recommendation performance. This shows that CitationNN can make full use of the information structure of the paper itself without additional external knowledge base to fully learn the citation relationship between academic papers, thus greatly improving the recommendation effect.

Dataset	Metrics	KGCN	KGAT	Simple-HGN	**CitationNN**
CiteULike	Recall@20	3.05	0.95	2.07	**5.43**
	Precision@20	0.48	0.19	0.31	**0.79**
	NDCG@20	1.64	0.61	1.08	**2.85**
	HR@20	7.94	3.08	4.97	**12.92**
DBLP	Recall@20	20.91	17.29	25.03	**x**
	Precision@20	2.20	1.83	2.60	**x**
	NDCG@20	11.33	9.25	14.90	**x**
	HR@20	36.37	30.95	42.00	**x**

Table 2. Performance comparison of CitationNN and Knowledge-Aware models across multiple datasets.

4.4 Summary

Overall, CitationNN achieved optimal performance on both CiteULike and DBLP datasets, and comprehensively outperformed MCAP and all existing models. Key benefits include: More efficient relationship modeling: Compared to MCAP, CitationNN further optimizes the way user-user and paper-paper relationships are modeled, allowing GNN to more deeply capture potential associations across papers and improve recommendation accuracy.

- Stronger generalization ability: On CiteULike and DBLP, two academic recommendation datasets with different characteristics, CitationNN always maintains optimal performance, indicating that it has good generalization ability.
- No external knowledge required: CitationNN relies only on the basic information of the paper to build a high-quality recommendation system, reducing additional data requirements and improving scalability compared to the knowledge-enhanced model.

5 ANALYSIS

5.1 Feasibility and Effectiveness Analysis

The modeling strategy relied on by CitationNN originates from the structural essence abstraction of academic citation behavior, and its core assumption - that citation and citation are semantically asymmetrical, and this asymmetry plays a decisive role in the information transmission path - is highly consistent with the generation logic of real academic networks. The model constructs bidirectional isomerization edges based on this premise, and realizes explicit distinction of reference semantics without introducing new node types, so that the directionality in the original structure can be retained, and the presentation inconsistency caused by the heterogeneous node types in traditional isomerization graphs can be avoided. This design ensures the model’s theoretical structure is closed and the output solution is analyzable, so it has good application feasibility.

In addition, CitationNN uses dual convolutional channels to independently model "cite" and "be cited", and through the combination form of shared node representation and differentiated aggregate function, it ensures that the direction semantics are preserved under the premise of controllable parameter number. This structure allows the model to learn the best path for information to travel through the network without explicit guidance, thereby reducing reliance on assumptions about path design and direction, and reducing the risk of model misattribution. Since all propagation strategies are determined by training data, CitationNN can adapt to learn reasonable aggregation patterns under different structural distributions, which is also verified by stable experimental results across data sets.

In terms of recommendation performance, the model performed stably on multiple real data sets with different densities and degrees of heterogeneity, and was superior to the baseline method in major indicators such as Recall, Precision, NDCG and Hit Rate. These improvements come not only from the modeling ability of citation direction, but also from the characterization of semantic dependence in the process of information selection. Through independent experiments under multiple rounds of random initialization, we observe that the model has very small variance on key indicators, indicating that it is less sensitive to random factors and structural perturbations, and can maintain consistent output under different conditions, which further supports its stability and reliability in recommendation tasks.

5.2 Evaluation Method Analysis

In this section, we evaluate the system developed in Section 3 and the results described in Section 4 with four criteria, Recall(Section 5.2.1), NDCG(Section 5.2.2), HR(Section 5.2.3) and Precision(Section 5.2.4). Recall, Normalized Discounted Cumulative Gain(NDCG), Hit Rate(HR) and Precision 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.

5.2.1 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 (12), 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.

$$\text{Recall@K} = \frac{|\text{Relevant Items} \cap \text{Recommended Items@}K|}{|\text{Relevant Items}|} \tag{12}$$

5.2.2 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' preferences for relevant papers at the top of the recommendation list. It can be expressed as Equations (13) to (15), 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.

$$\text{DCG@K} = \sum_{i=1}^{K} \frac{2^{\text{rel}_i} - 1}{\log_2(i+1)} \tag{13}$$

$$\text{IDCG@K} = \sum_{i=1}^{|REL|} \frac{2^{\text{rel}_i} - 1}{\log_2(i+1)} \tag{14}$$

$$\text{NDCG@K} = \frac{\text{DCG@K}}{\text{IDCG@K}} \tag{15}$$

5.2.3 Hit Rate. Hit Rate (HR) measures whether at least one of the relevant papers appears in the top-K recommended list. Unlike Recall and Precision which consider the proportion of relevant items, HR is a binary indicator for each user and provides a coarse but intuitive measure of recommendation success. It reflects the model's ability to ensure that users will find at least one useful item among the recommendations. The formula is shown in Equation (16), where $Hit@K$ equals 1 if there is at least one relevant item in the top-K recommendations, and 0 otherwise.

$$\text{HR@K} = \frac{1}{|U|} \sum_{u \in U} \mathbb{I}(|\text{Relevant Items}_u \cap \text{Recommended Items}_u@K| > 0) \tag{16}$$

5.2.4 Precision. Precision measures the proportion of recommended items in the top-K list that are actually relevant. It evaluates how many of the recommended papers are truly useful to the user, which reflects the recommendation system's ability to reduce noise and improve result quality. Precision complements Recall by emphasizing specificity over coverage. The formula is provided in Equation (17), where $RelevantItems$ is the set of ground-truth relevant items, and $RecommendedItems@K$ is the set of top-K recommended items.

$$\text{Precision@K} = \frac{|\text{Relevant Items} \cap \text{Recommended Items@}K|}{K} \tag{17}$$

5.3 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, NDCG, HR and Precision(Sections 5.2.1 to 5.2.4) will be used to verify whether the model is effective in academic recommendation tasks.

This chapter concludes the work carried out during the project. In the next chapter, Section 6, we discuss our findings and their implications.

6 DISCUSSION

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

6.1 Professional Issue

6.1.1 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.

6.1.2 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.

6.2 Legal Issue

6.2.1 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.

6.2.2 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.

6.3 Ethical Issue

6.3.1 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.

6.3.2 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.

6.4 Social Issue

6.4.1 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.

6.4.2 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 CONCLUSION

In this section, we will summarize the actual contribution of the model we proposed and explore the limitations and the potential further work based on the current model.

7.1 Actual Contributions

CitationNN has demonstrated a full range of performance advantages in academic paper recommendation tasks, achieving stable and significant performance improvements on multiple metrics and datasets compared to existing mainstream models, including matrix decomposition, graph neural networks, and knowledge enhancement methods. By introducing the modeling strategy of bidirectional heterogeneous edges and double convolution kernel, CitationNN can capture both "referenced" and "referenced" information transmission semantics, thereby building a more complete and directional sensing paper representation, which makes up for the shortcomings of the traditional GNN model in understanding citation semantics.

It can be observed from the experimental results that our model shows clear advantages in all kinds of evaluation indicators, and its performance is steadily higher than that of the existing representative models. This difference in performance reflects that the model's ability to extract structural semantics in academic recommendation scenarios no longer relies on a single interactive perspective, but can simultaneously perceive the potential contribution relationship in multiple information sources.

The proposed method has better semantic resolution and adaptability to structural variation. Especially in the scenario where the relationship between the user and the paper is sparse and it is difficult to make effective judgment purely based on interaction, the advantages of the model show that it can effectively supplement the shortcomings of traditional collaborative signals and broaden the sources of recommendation basis. Comparing the bias of different types of models in various indicators, CitationNN maintains stable advantages in multiple indicators at the same time, which further indicates that the constructed representation can strike a balance under multi-dimensional requirements, avoid the problem of overfitting for a single task, and improve the reliability and versatility of the recommendation system in practical applications.

The modeling core that CitationNN relies on, semantic deconstruction of asymmetric interaction through bidirectional heterogeneous edges, is portable across scenes. On the premise of independent node type change, we can adapt to other graph network scenarios with structural directionality or semantic asymmetry only by the edge direction and semantic distinction. In essence, this design abstracts the representation offset of the two behavioral roles of "active initiation" and "passive reception", and allows the offset to be independently modeled by the differential graph convolution kernel in the training process, so it has the basis for semantic generalization.

Take the subscription relationship in social networks as an example, the "follow" behavior among users is typically unidirectional. The initiator usually selects the subscribed object based on interest, while the recipient's behavior has nothing to do with the relationship. The traditional approach to this kind of network often uses undirected edge modeling, which makes the recommendation task unable to distinguish the semantic roles of the two types of nodes: "paid a lot of attention" and "paid a lot of attention to others". In this scenario, the proposed method can naturally model "follow" as a side pair with clear direction and semantic independence, and learn the behavior-driven differential representation of the two types of nodes through a bilateral structure similar to "cite/be cited" and an independent aggregation process, so as to effectively capture the propagation direction and semantic distribution of social influence.

In neurobiological networks, synaptic connections between cells constitute a typical structure of directed interaction. There are physical and semantic asymmetries between the sending and receiving of neuronal signals, such as presynaptic cells producing neurotransmitters and postsynaptic cells responding to them. This unidirectional flow of information is highly corresponding to "active citation" and "passive citation" in academic citation relationships, and the representation shift caused by the different functional roles of upstream and downstream nodes. The proposed model can model the synaptic connection as a semantically explicit bidirectional isomeric edge, and use the dynamic direction selection mechanism to learn the upstream and downstream representation evolution mechanism of neurons according to the neural activity map, so as to have the ability to model the neural regulatory transmission mechanism.

It is precisely because the model takes semantic directionality as an explicit structural component of the edge level, and allows edge pairs to be separated in the parameter space for modeling, that it can generalize across application fields to any interactive network with recognizable directional semantic structure without changing the node type or the overall topology. This modeling strategy for asymmetric behavior semantics not only improves the judgment ability in recommendation tasks, but also provides a general solution for information transfer modeling in structural behavior networks.

7.2 Limitations and Future Work

Although the current CitationNN model has been able to effectively model asymmetric relationships in citation networks and achieve good recommendation results, it still has certain limitations in capturing the dynamics of influence propagation and supporting large-scale data scenarios in actual academic networks. On the one hand, the existing models rely on explicit reference data for edge construction and information aggregation, and it is difficult to deal with important relationship omissions caused by incomplete references, missing data or semantic dislocation. In addition, there is not always a consistent relationship between the direction of influence concentration and the direction of actual citations. Especially in the case that high-quality literature citation strategies are relatively conservative and low-quality literature citation randomness is relatively large, the side weights and directions established by CitationNN cannot accurately correspond to the actual flow mode of influence in the real context. This will limit the model's ability to find potentially high-value nodes. On the other hand, the reference network itself is highly dense in scale and has a huge number of nodes. In practical applications, the memory of a single CUDA device often fails to accommodate the complete graph structure, which makes it difficult to directly extend the model to the full-graph recommendation task in industrial academic platforms or social networks.

In order to further improve the semantic integrity and computational scalability of the model, it can be extended from three aspects in the future. First of all, aiming at the problem of incomplete reference side information and missing key references, semantic modeling of paper title and abstract can be carried out in combination with large language model (LLM) to predict potential hidden reference relationships, so as to assist GraphLearner model to complete the missing neighbor nodes and information path, and improve the semantic expression integrity of graph structure. Secondly, the GraphSAGE[Hamilton et al. 2017] technology can be used to replace the original heterograph convolution mechanism, reduce the interference of non-critical nodes on representation learning through neighbor subsampling and aggregation operations, and control the computing load of the model, and retain the neighbor information with high semantic relevance to focus on effective propagation channels. On this basis, combined with the federated learning framework, the whole reference network is segmented into parallel subgraphs to achieve efficient training across multiple CUDA devices, so as to ensure the deployability of the model in large-scale scenarios. Such designs will enable our models to support input sizes comparable to large-scale language models, with the same level of semantic modeling power and practical application potential.

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