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ABSTRACT

Recommendation systems play an important role in modern day digital applications such as eCommerce, video streaming, and social networks by allowing users to find relevant information amidst large datasets. Classical recommendation methods such as Collaborative Filtering and Matrix Factorization suffer from certain limitations such as sparse data, cold start problems, scalability issues, and privacy concerns due to centralization of datasets. To overcome these problems, we propose an approach to building a privacy-preserving recommendation system based on Federated Light Graph Convolutional Networks along with temporal modeling and federated weighted aggregation. The proposed approach uses recent interactions for more significant influence on user preferences and uses weighted federation for aggregating models based on the size of client datasets. The experiments were conducted on the MovieLens 32M dataset, where performance is measured using Precision@10, Recall@10, and NDCG@10. From our experimental evaluations, the proposed method has shown improvements of 13%, 16%, and 12% in Precision@10, Recall@10, and NDCG@10, respectively, compared to a baseline federated model. At the same time, the proposed method preserves privacy of users' personal data. It is found that the integration of LightGCN, temporal modeling, and federated learning offers an effective and scalable solution to modern recommendation systems.

Keywords: Recommendation Systems, Federated Learning, LightGCN, Temporal Modeling, Privacy-Preserving Recommendation.

CHAPTER 1

INTRODUCTION

1.1 Overview of Recommendation Systems

The recommendation system is an essential component of modern digital services that include websites like online shopping sites, streaming video services, social media sites, online education platforms, and intelligent information delivery apps. The increase in the number of internet users and service providers results in a massive amount of data being produced every day, which makes it difficult for people to locate items, services, or even content that may interest them. Information overload happens when individuals are unable to filter useful information related to themselves from an enormous amount of information that exists. Recommendation systems help overcome the challenge of information overload by giving personal recommendations according to the user's interests and actions [23].

Traditional methods such as Collaborative Filtering, Content-based filtering, and Matrix Factorization have been commonly used due to their effectiveness and simplicity. Collaborative Filtering is responsible for finding users or items having similar interests and then recommending items based on their behaviors, while Content-based Filtering concentrates on item and user features. The method of Matrix Factorization enhances recommendation by modeling the latent feature spaces of both items and users [23, 62]. Despite their success, there are a number of drawbacks associated with traditional methods, among which data sparsity problem, cold start problem, lack of scalability, and complex modeling of user item interaction are the most significant [53].

The rise of artificial intelligence and deep learning technologies has helped advance recommendation systems significantly. Models such as CNN, RNN, LSTM, and GNN models have enhanced the performance of recommendation systems through learning intricate relationships between different variables. Of these techniques, graph neural networks are some of the best performing ones since recommendation

data is inherently graph based and involves interactions between items and users. An example of a well-performing graph-based recommendation system is LightGCN, which is better than the regular graph convolutional network because it has distilled all the components down to the basics by avoiding the inclusion of any extraneous features and non-linear activations [17].

Federated Learning (FL) is one approach that may be used to solve this problem as it allows the clients to collectively train the global model without exposing any raw information about their data. FL involves local training by the clients using their private information; however, the parameters of the model are shared with the central server. Such a machine learning technique improves the level of privacy of the system but still retains the quality of recommendations. However, there are several limitations in federated recommendation systems, including the problems related to non-IID data, communications costs, and aggregation schemes [55].

One of the other limitations associated with existing recommendation systems is the assumption that the preferences of the users remain unchanged throughout. This is not true since, in reality, the preferences of users change due to their actions in the recent past, trending topics, seasonality, and context awareness. The traditional recommendation models face challenges in dealing with this aspect, thus affecting the performance of the recommendation systems. Temporal recommendation models solve this problem by assigning greater importance to recent actions and reducing the importance of older actions.

The thesis explores the development of a privacy-preserving recommendation algorithm using Federated LightGCN with temporal modeling and weighted federated aggregation techniques. The objective is to improve recommendation precision while providing adequate privacy guarantees and better adaptation to changing user preferences.

1.2 Motivation

The rapid growth in the use of digital platforms like e-commerce platforms, entertainment portals, social networking sites, and learning platforms has significantly increased the amount of information available to users. As such, users often find themselves having difficulties identifying items that align with their tastes. The advent of recommendation systems has become indispensable when it comes to tackling this problem through personalized recommendations. However, many of the existing recommendation systems still rely on centralized databases and collaborative filtering methods, which have several constraints.

One of the key aspects that must be considered in the case of today's recommendation systems is data privacy. In order for centralized recommendation algorithms to work properly, they require users to provide a lot of sensitive information like their browsing history, purchase details, ratings and reviews, as well as their behavior pattern. In this way, the possibility of data leakage, abuse and access by third parties rises considerably. Taking into account the increasing importance of privacy laws and people's awareness regarding them, there is clearly a need for more private recommendation algorithms [54].

The other significant problem is that there exists non-IID (non-independent and non-identically distributed) data among users. In practice, different users will interact with different kinds of products according to their individual tastes, thus leading to significant heterogeneity in data distribution. Conventional centralized models and classical federated aggregation approaches like FedAvg are inadequate in dealing with such data heterogeneity, thus making it difficult for them to converge effectively [18].

Apart from the issues of privacy and data heterogeneity, traditional recommendation systems are based on the assumption that there is no change in the preferences of users over time. This is not true because users' preferences keep changing constantly owing to recent activity, seasonality, context, and changing individual requirements. Failure to address this challenge makes recommendations less relevant and hinders users' satisfaction levels.

Recommendation methods that use graphs, such as LightGCN, have proven effective when applied to recommendation datasets because it is natural for recommendation datasets to take on graph structures. On the other hand, Federated Learning provides a technique to train models privately without compromising model accuracy. Combining these two approaches with temporal-aware modeling and improved aggregation strategies creates an opportunity to build more efficient, scalable, and secure recommendation systems.

Motivation behind this research is to tackle the mentioned issues and propose a recommendation approach that uses Federated Learning, LightGCN, temporal models, and weighted federated aggregation. Recommendation quality and strong privacy will be achieved, and problems associated with non-IID client data and dynamics of user preferences will be taken into account.

1.3 Research Objectives

The main objectives of this research work are as follows:

1.4 Objectives of the Research

The main objectives of this research work are as follows:

- To develop a privacy-preserving recommendation system using Federated Learning and LightGCN for generating accurate personalized recommendations.
- To overcome the limitations of traditional centralized recommendation systems such as privacy risks, scalability issues, and non-IID client data distribution.
- To improve recommendation accuracy by incorporating temporal-aware pre-processing that emphasizes recent user interactions.
- To enhance global model convergence and learning efficiency using weighted federated aggregation based on client data size.
- To evaluate the effectiveness of the proposed model on the MovieLens 32M dataset using Precision@10, Recall@10, and NDCG@10 metrics.

1.5 Scope

In this thesis, we try to build a privacy-preserving recommendation model through Federated Learning and LightGCN for recommendation purposes. The project mostly deals with user-item interactions and also employs temporal-based preprocessing due to varying preferences of users with time. The federated learning method is used to ensure decentralized model training, where user data remains on local clients and only model parameters are shared for global aggregation. Weighted Federated Averaging is used to improve aggregation performance in the presence of non-IID client data distributions.

The experimental evaluation of the proposed model is performed using the MovieLens 32M dataset, which provides large-scale user-item interaction records along with timestamp information. The performance is measured using standard recommendation metrics such as Precision@10, Recall@10, and NDCG@10. The work is limited to recommendation tasks based on explicit user interactions and does not

include advanced explainable recommendation methods, cross-domain recommendation, or real-time online deployment in production systems.

1.6 Thesis Outline

This thesis is organized into six chapters. The chapter 1 focuses on the introduction to the research project, which involves the introduction of recommendation systems in general, reasons for conducting the research, objectives of the research, scope of the study, and contribution of the current research. Chapter 2 highlights a comprehensive review of traditional recommendation systems, graph-based recommendation systems, federated recommendation systems, and developments in recent times in terms of privacy preservation in recommendation. It will also discuss the limitations of the existing techniques and the research gap that the proposed research is focusing on. Chapter 3 deals with the methodology adopted to conduct this research; it will discuss the proposed Federated LightGCN based recommendation model with temporal modeling and federated weighted aggregation. Chapter 4 describes the implementation methodology used in the proposed system. The chapter elaborates on the data sets used, pre-processing of data, the method used to split clients, hyperparameters and their values, and finally describes the entire experimental setup used in training and testing the model. Chapter 5 contains the results of the experiments carried out using the proposed recommendation system. The chapter uses performance measures such as precision at 10, recall at 10, and NDCG at 10. It also compares the system with other baselines and explores the effects of weighted aggregation and temporal modeling. Chapter 6 summarizes this thesis.

CHAPTER 2

LITERATURE REVIEW

Recommendation systems are advanced information filtering technologies that aim to understand the preferences of a particular user and provide recommendations based on their previous actions and behavior. Recommendation systems have found wide application in today's world and have been integrated into several online platforms including online stores, video streaming websites, social networks, news sites, and e-learning platforms. Their primary objective is to reduce information overload by helping users discover products, movies, music, articles, and services that match their interests and needs.

A recommendation system analyzes historical user-item interactions such as ratings, clicks, purchases, browsing history, and feedback to generate personalized suggestions. Depending on the application domain, different recommendation techniques are used to improve recommendation quality, scalability, interpretability, and user satisfaction. Over the years, recommendation systems have evolved significantly from simple collaborative filtering approaches to advanced graph-based, federated, and temporal-aware intelligent systems.

In this research work, the literature survey of recommendation systems is conducted based on five major criteria that represent the evolution of recommendation technologies and the current state-of-the-art approaches in recommendation research. These five categories are:

1. Traditional Recommendation Systems
2. Deep Learning Based Recommendation Systems
3. Graph-Based Recommendation Systems
4. Federated Recommendation Systems
5. Temporal Modeling in Recommendation Systems

Traditional recommendation systems mainly include collaborative filtering, content-based filtering, and matrix factorization methods, which form the foundation of modern recommender systems. Deep learning based methods improve recommendation performance by learning complex non-linear user-item relationships using neural networks. Graph-based recommendation systems model user-item interactions as graphs and apply Graph Neural Networks such as LightGCN to capture higher-order connectivity patterns. Federated recommendation systems focus on privacy-preserving model training by keeping user data on local devices instead of centralized servers. Temporal modeling methods improve personalization by considering the dynamic nature of user preferences and assigning higher importance to recent interactions. The overall classification of recommendation system approaches covered in this research work is illustrated in Fig. 2.1.

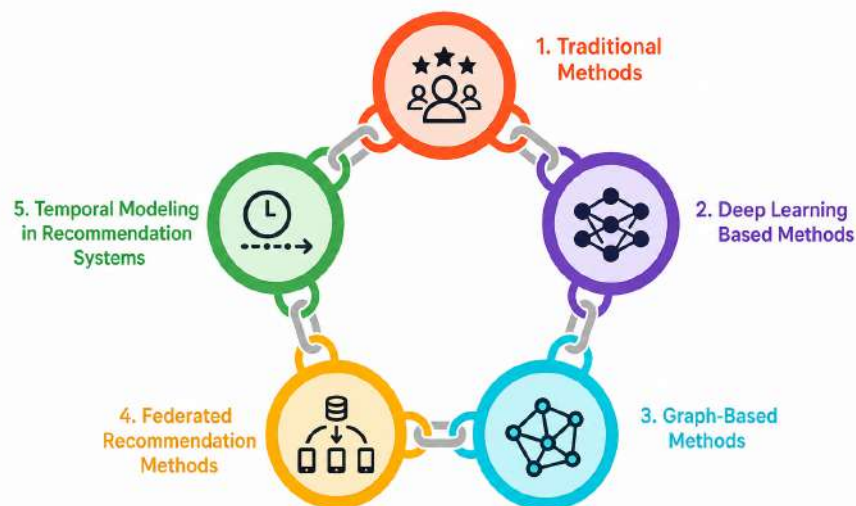


Figure 2.1: Recommendation System Approaches Covered in Literature Review

2.1 Traditional Recommendation Systems

Conventional recommendation methods play a vital role in the development of personalized information filtering techniques in today's digital technologies, including e-commerce websites, online streaming services, learning platforms, and social media platforms. The primary purpose of recommendation methods is to overcome information overload by providing relevant recommendations to users according to their likes and past interaction behaviors. Some of the earliest and popular recommendation methods include CF, CBF, and MF. In one of their experiments, Xu et

al. examined the concept of federated learning-based social recommendation with social denoising [66].

Collaborative Filtering is one of the most popular recommendation methods since it does not need explicit item features but depends heavily on user-item interaction history. Item-to-item collaborative filtering was introduced by Linden et al. at Amazon.com [29]. They showed that calculating similarities between items can scale well to big data and serve as the foundation for industry recommendation pipelines. The idea is to find similarities among users or items and make recommendations according to their common interests. In user-based collaborative filtering, recommendations will be made for items that are favored by similar users. Meanwhile, in item-based collaborative filtering, recommendations are made based on items that are similar to the ones that were favored by the targeted user. A systematic review of the advances in collaborative filtering was conducted by Koren et al. which was included in the Recommender Systems Handbook [23]. Even though the technique is straightforward and powerful, it usually suffers from data sparsity and cold-start issues when new users or new items enter the system. Accuracy-oriented neural recommendation was reviewed extensively by Wu et al. [62].

Content-Based Filtering utilizes the features of the objects and the preferences of the users themselves. In Content-Based Filtering, recommendations are made through matching the features of the object, which can be genre, type, description, or keywords, to the previous preferences of the user. This method works best if there is enough information regarding the object; otherwise, it cannot provide recommendations. It may have problems with variety because it always recommends similar objects.

Matrix Factorization enhances recommendation capabilities through the representation of users and items in a common latent feature space. Matrix factorization involves reducing the user-item interaction matrix into a low-dimensional feature vector capturing the underlying relationship between the users and items. In their study, Ampazis et al. developed a constrained optimization-based approach for matrix factorization, showing improved accuracy when making recommendations from social rating networks [3]. This model became highly successful in recommending large amounts of data because of its efficiency and effectiveness. Nevertheless, traditional approaches to matrix factorization continue to encounter problems such as handling dynamic preferences of users, sparse interactions, and privacy issues in centralized systems. To address this problem, Wang et al. introduced an approach combining users-context collaborations and tensor factorization in social recommendations based on GNNs [53].

In order to enhance the recommendation performance, there are usually several methods that can be utilized in hybrid recommendation systems, such as collaborative filtering, content-based filtering, and rule-based filtering. They are designed to overcome the limitations associated with each method. For example, Liu and Zhang introduced a personalized recommendation model for e-commerce websites by using the association rule algorithm, resulting in an enhanced accuracy rate of the recommendation [30]. In addition, Pan et al. presented a recommendation model for university libraries through hybrid collaborative filtering [40]. Although these efforts have achieved satisfactory performance, existing recommendation algorithms are difficult to incorporate the modeling of users' complicated behaviors.

2.2 Deep Learning Based Recommendation Systems

The shortcomings of the conventional recommender system approaches like collaborative filtering and matrix factorization have prompted researchers to look at deep learning approaches to improve recommendation precision and personalization. The deep learning approach has the ability to learn intricate non-linear dependencies from big user-item interaction datasets, which makes it an appropriate choice for today's recommender systems. As mentioned by Wu et al. , these approaches offer more efficient representation learning and have the capability to manage sparse data and hidden behaviors, which are difficult for conventional approaches [62].

Convolutional neural networks (CNNs) have been extensively applied to recommendation systems for learning salient features from text-based information, pictures, and user behavior patterns. Wang et al. introduced a personalized recommendation system in an e-commerce environment using big data technology, highlighting how deep learning models, combined with big data infrastructure, can effectively enhance recommendation precision and coverage [56]. Recommendation systems that utilize CNN models are especially suited to e-commerce applications because of their reliance on image-based information and product descriptions for recommendations. Luo developed an efficient e-commerce personalized recommendation system combining the matrix factorization and CNN models, demonstrating the effectiveness of incorporating matrix factorization techniques along with CNN-based feature extraction algorithms to boost recommendation precision [36].

Recurrent Neural Network (RNN) and LSTM recommendation algorithms are frequently used in sequential and session-based recommendations. The research conducted by Li et al. [27] explores recommendation algorithms on user behavior sequence of e-commerce. This study shows how sequential analysis of users' behavioral

history helps to improve next item prediction accuracy. The main idea behind such recommendation approaches is to predict future actions based on the analysis of chronological order of users' actions. LSTM-based recommendation algorithms are particularly useful in prediction of users' upcoming interactions because of their ability to learn long-range dependencies.

Models that have incorporated hybrid techniques by integrating neural networks, collaborative filtering, and matrix factorization have also exhibited promising results. Kumar et al. [24] proposed an approach to increase the efficiency of recommendation systems using deep learning methods in e-commerce applications by incorporating diverse deep learning modules in order to increase the diversity and personalization in recommendations.

Even though deep learning algorithms greatly enhance the performance of recommendations, they usually need a lot of computational power and centralized training. Rawat et al. [46] recognized and investigated the main problems associated with e-commerce recommenders, such as scalability problems, sparsity problems, and privacy problems due to centralized deep learning models. Thus, it poses privacy problems and scalability problems, particularly in production environments. Such problems have motivated the scientific community to look for alternatives based on graphs and federated recommendation systems that ensure privacy and performance simultaneously.

2.3 Graph-Based Recommendation Systems

Recommendation models using graphs have proven to be among the most efficient techniques for capturing the complicated relations among users and items. When it comes to recommendation applications, it is easy to observe that relations among users and items can be represented using a bipartite graph, with users and items forming nodes and their interactions, such as rating, clicking, purchasing, or watching, forming edges. A comparison analysis of recommender systems using graph neural networks was carried out by Hamidi et al. showing that graph-based recommendations outperform standard matrix manipulations [15].

The performance of recommendations has greatly been enhanced by the use of Graph Neural Networks (GNNs) in capturing informative representations on graphs. Fan et al. introduced a graph neural network approach to social recommendation where the model is capable of incorporating the user-item interaction features as well as the social relations to form meaningful embeddings that capture user interests and item attributes [13]. Graph Convolutional Networks (GCNs) are one of the most

popularly applied types of GNN models in the domain of recommendation systems due to their efficient information diffusion on connected nodes. Wang et al. [57] designed Neural Graph Collaborative Filtering (NGCF), where the collaborative signals were captured directly within the embedding generation procedure using higher-order propagation on the graph.

Light Graph Convolutional Network (LightGCN) is an efficient and simple variant of the graph neural network model tailored explicitly to collaborative filtering. LightGCN was introduced by He et al. through the elimination of the redundant layers of feature transformation and activation functions in conventional GCNs, retaining only the layer-wise propagation process [17]. The LightGCN model generates embeddings for both users and items by performing information propagation between multiple layers of the graph and integrating the embeddings from various layers.

Recently, there have been many advancements in graph-based recommendation techniques through the addition of more relationships like social relationships, knowledge graphs, and cross-domain relationships. For instance, Hao et al. proposed a novel technique called the federated knowledge-enhanced graph attention network for privacy-preserving social recommendations [16]. It was found that the addition of knowledge graphs to the graph attention networks improved recommendation accuracy without compromising privacy. Similarly, Yang et al. developed a novel graph neural network model called DGRec for diverse embedding generation in recommendation systems, which led to improvements in recommendation coverage and reduced specialization [68].

Despite the effectiveness of these models, current approaches continue to depend on a centralized database for storing information and training the model. This poses privacy concerns and restricts the application of these techniques in real-world scenarios. To overcome such issues, researchers have combined federated learning with graph-based recommendations systems.

2.4 Federated Recommendation Systems

The application of federated recommendation systems has been of considerable interest as an efficient way of protecting the privacy of users. The main disadvantage of centralized recommendation algorithms is that all the information related to users, such as browsing activities, ratings, purchases, and interactions, is available at the central server, leading to several privacy and security threats. FedAvg, proposed by McMahan et al. [38], is considered one of the most basic approaches in federated learning, where clients collaboratively train a global model using their

model weights. Federated Learning addresses this issue by allowing multiple clients to collaboratively train a global recommendation model without sharing their raw local data. Zheng et al. [71] proposed federated matrix factorization recommendation based on secret sharing for privacy preservation, demonstrating that combining federated learning with cryptographic techniques improves both privacy and recommendation quality in distributed environments.

Ammad-Ud-Din et al. [1] were among the first to propose federated collaborative filtering for privacy-preserving personalized recommendation systems, showing that federated training can achieve competitive recommendation performance while keeping user data on local devices. Chai et al. [7] developed a secure federated matrix factorization method and demonstrated that secure aggregation protocols can be applied effectively to collaborative recommendation without sacrificing accuracy. Wu et al. [65] proposed FedGNN, a federated graph neural network for privacy-preserving recommendation, extending the federated learning paradigm to graph-structured recommendation models and showing strong performance on benchmark datasets.

While there is no denying their strengths, federated recommendation models encounter some practical obstacles, including non-independent and non-identically distributed (non-IID) client datasets, increased communication costs, and ineffective aggregation techniques. Traditional aggregation methods, such as FedAvg, fail to achieve good results when there is significant heterogeneity in client user behavior. He et al. [18] have proposed a co-clustering technique for federated recommender systems, which solves the problem of non-IID data distribution in a way that improves convergence of the global model by partitioning clients into groups with similar distributions. Luo et al. [35] have presented an improved personalized federated recommendation algorithm, PerFedRec++ that uses self-supervised pre-training of local models. They found that additional self-supervised auxiliary tasks boost the performance of local models in case of heterogeneous data. Li et al. [26] have proposed federated recommendation with additive personalization, proving that adding personalization layers increases recommendation performance without compromising the privacy provided by federated learning.

2.5 Temporal Modeling in Recommendation Systems

It is a significant part of the contemporary recommendation system due to the fact that users' behavior is not constant but dynamic over time. The standard assumption in recommendation modeling has been that user interests are constant

and unchanging, which lowers their relevance when recommending items in real-life cases as a result of the dynamic interests caused by new activities, seasonality, and context.

Sequencing models including Recurrent Neural Networks (RNNs), LSTM, and session-based recommendation algorithms are well suited for detecting temporal dependencies in sequential recommendation. Tian et al. [52] present an approach to denoising unreliable interactions in graph collaborative filtering to improve learning from temporal preferences by excluding noisy or outdated interactions. Additionally, Wang et al. [61] introduce denoised self-augmented learning for social recommendation through a time-aware augmentation strategy, allowing the model to better detect evolving user preferences for improved recommendations. The sequential models give greater weightage to recent interaction sequences while decreasing the effect of old interaction sequences over time. With the aid of temporal-aware pre-processing techniques, the recommendation system is able to concentrate more on the current user preferences which is helpful in changing environments like e-commerce, video streaming, and social media recommendation systems.

2.6 Research Gap

Despite the considerable advancements achieved in recommendation systems using approaches like collaborative filtering, deep learning, graph neural networks, and federated learning, some critical issues persist and have not been resolved. The vast majority of the conventional and deep learning-based recommendation system models employ centralized data storage. This leads to severe privacy concerns, making it difficult to deploy them in real-world applications with strict privacy requirements. Even with the federated recommendation model, the existing aggregation techniques, including FedAvg, fail to manage non-IID data distribution across clients, resulting in inadequate convergence and degraded recommendation results. Sun et al. [48] conducted an exhaustive literature review of federated recommendation systems, citing non-IID data distribution and inefficient communication as the two main unresolved issues within the realm of federated recommendation systems. Wang et al. [55] developed personalized federated contrastive learning for recommendations, tackling the problems introduced by heterogeneity in clients' datasets while noting the lack of research on the temporal aspect of federated recommendation systems.

Other than this, one other important limitation relates to ineffective modeling for temporal information within federated recommendation systems. Most of the models

do not address the aspect of dynamicity within users' behavior. This reduces recommendation relevance and personalization quality. In addition, many graph-based federated recommendation systems focus mainly on privacy preservation while giving less attention to temporal preference changes and weighted aggregation strategies. Therefore, there is a strong need for a recommendation method that combines Federated Learning, LightGCN, temporal-aware modeling, and weighted aggregation to improve both privacy preservation and recommendation performance.

2.7 Summary of Existing Systems

Traditional RSs rely heavily on centralised processing, limiting scalability and privacy guarantees. Luo [36] demonstrated the benefits of combining CNN and matrix factorization for high-performance e-commerce recommendations, while Pan [41] designed a real-time e-commerce recommendation system using Apache Spark in the context of big data, showing that distributed computing infrastructure improves system scalability and response time. Domain-specific systems such as university library recommenders have shown promise, but full integration of deep, reinforcement, and federated learning remains underexplored. Table 2.1 shows the comparison of major Recommendation Algorithms.

Table 2.1: Comparison of Major Recommendation Algorithm Approaches

Approach	Typical Models	Advantages	Limitations
Collaborative Filtering	User/Item based CF, SVD, MF	Simple, interpretable, strong baselines, efficient on sparse data	Struggles with cold start, ignores content/context, mostly static
Content Based	TF-IDF, shallow neural encoders	Works for new items, leverages attributes, user-specific explanations	Overspecialisation, limited use of collaborative signal
Deep Learning	Neural CF, CNN/RNN/Transformer models	Captures non-linear interactions, fuses multiple modalities	Requires large datasets, prone to overfitting, heavy computation
Reinforcement Learning	DQN, Policy Gradient, SlateQ	Optimises long-term objectives, adapts to feedback	Difficult exploration, large action space, challenging offline evaluation
Federated Learning	Federated MF, Federated NCF	Privacy preserving, compliant with regulations	Communication cost, client heterogeneity, complex debugging

Table 2.2 presents a consolidated summary of the key studies reviewed in this chapter, highlighting the datasets used, algorithms and technologies employed, key results reported, and the respective advantages and limitations of each approach.

Table 2.2: Summary of Key Studies in Recommendation Systems Literature

Author(s)	Year	Dataset	Algorithm / Technology	Result	Advantage	Disadvantage
Linden et al. [29]	2003	Amazon product data	Item-to-item Collaborative Filtering	Scalable real-time recommendations deployed at Amazon	Highly scalable; works well on sparse data	Cold-start problem; no content awareness
Koren et al. [23]	2021	Netflix Prize, MovieLens	Matrix Factorization (SVD, SVD++)	State-of-the-art accuracy on Netflix Prize dataset	Handles implicit feedback; efficient	Static preferences assumed; privacy risks
He et al. [17]	2020	MovieLens-1M, Gowalla, Yelp2018, Amazon-Book	LightGCN	Outperforms NGCF by ~9% on Recall@20	Computationally simple; strong performance	Ignores temporal dynamics; centralized training
Wang et al. [57]	2019	Gowalla, Yelp2018, Amazon-Book	NGCF (Neural Graph Collaborative Filtering)	Significant gain over MF baselines on Recall and NDCG	Captures high-order connectivity	High complexity; no privacy guarantees
Wang et al. [59]	2019	Amazon (book, movie), Last-FM	KGAT (Knowledge Graph Attention Network)	Improved AUC and F1 over baseline GNN methods	Integrates knowledge graph signals	Requires rich knowledge graph; expensive to build
Fan et al. [13]	2019	Ciao, Epinions	GraphRec (GNN for Social Rec.)	Better MAE and RMSE than social CF baselines	Incorporates social trust signals	Requires social graph data; limited scalability
Wu et al. [63]	2019	Ciao, Epinions, Flickr	DiffNet (Neural Influence Diffusion)	Improved HR and NDCG over social MF methods	Models dynamic social influence propagation	Assumes static social graph; centralized
Wu et al. [62]	2022	Multiple benchmark datasets	Survey (CF, NCF, GNN, Transformer)	Comprehensive taxonomy of neural recommendation	Broad coverage of techniques	Survey only; no novel experimental results

Author(s)	Year	Dataset	Algorithm / Technology	Result	Advantage	Disadvantage
McMahan et al. [38]	2017	CIFAR-10, Shakespeare text	FedAvg (Federated Averaging)	Reduced communication rounds by $10\times-100\times$	Privacy-preserving; communication-efficient	Poor convergence on non-IID data
Ammad-Ud-Din et al. [1]	2019	MovieLens-1M	Federated Collaborative Filtering	Competitive accuracy with centralized CF	User data stays local; privacy preserved	Performance gap vs. centralized; cold-start issue
Chai et al. [7]	2021	MovieLens, Epinions	Secure Federated Matrix Factorization	Maintained MF accuracy with strong security guarantees	Secure aggregation with encryption	High computational cost; communication overhead
Zheng et al. [71]	2024	MovieLens, Douban	Federated MF with Secret Sharing	High accuracy with strong privacy guarantees	Privacy via cryptographic secret sharing	High communication and computation cost
He et al. [18]	2024	MovieLens-1M, Amazon	Co-clustering for Federated RS	Better convergence than FedAvg on non-IID data	Handles data heterogeneity effectively	Clustering overhead; scalability concerns
Luo et al. [35]	2023	MovieLens-1M, Amazon	PerFedRec++ (Self-supervised Pre-training)	Improved NDCG and Hit Rate over FedAvg baselines	Personalized; self-supervised auxiliary learning	Complex training pipeline; longer pre-training time
Li et al. [26]	2023	MovieLens-1M, Epinions	Federated Recommendation with Additive Personalization	Improved Recall and NDCG with personalized layers	Better personalization in federated setting	Additional parameters per client; memory overhead
Hao et al. [16]	2024	Ciao, Epinions	Federated Knowledge-enhanced GAT	Outperformed federated baselines on HR and NDCG	Integrates knowledge graph in federated setting	Requires knowledge graph; complex integration

Author(s)	Year	Dataset	Algorithm / Technology	Result	Advantage	Disadvantage
Yang et al. [68]	2023	MovieLens, Yelp, Amazon	DGRec (Diversified Embedding GNN)	Higher diversity and accuracy than LightGCN	Improves recommendation diversity	More complex training; higher memory usage
Tian et al. [52]	2022	MovieLens, Yelp, Amazon	Denoising Graph CF	Improved Recall@20 and NDCG@20 on noisy datasets	Robust to interaction noise and outliers	Denoising adds training complexity
Wang et al. [61]	2023	Ciao, Epinions, Yelp	Denoised Self-Augmented Learning	Improved HR and NDCG over social recommendation baselines	Temporal-aware denoising augmentation	Sensitive to hyperparameter tuning
Luo [36]	2023	E-commerce product dataset	MF + CNN	Higher Precision and Recall than pure MF or CNN	Fuses content and collaborative signals	Requires image/text features; high training cost
Pan [41]	2025	E-commerce transaction data	Spark + Real-time CF	Low-latency real-time recommendations at scale	Scalable big data pipeline; low latency	Infrastructure heavy; limited personalization depth
Sun et al. [48]	2025	Survey across multiple datasets	Federated RS Survey	Identified key open challenges in federated RS	Comprehensive review of privacy and accuracy tradeoffs	Survey only; no new experimental contribution
Wang et al. [55]	2025	MovieLens, Amazon	Personalized Federated Contrastive Learning	Improved Recall and NDCG over FedAvg baselines	Contrastive learning improves local model quality	High communication rounds; complex objective
Hamidi et al. [15]	2024	MovieLens-100K, Amazon	GNN Comparative Study (GCN, GAT, GraphSAGE)	GAT achieved best RMSE among compared GNN models	Provides systematic GNN comparison for recommendation systems	No novel model proposed; limited dataset variety

CHAPTER 3

PROPOSED METHODOLOGY

This federated recommendation model is built upon the Light Graph Convolutional Networks (LightGCN). The whole design aims at decentralizing the learning process, temporal aware modeling, and integrating an explainability module while preserving the user privacy.

3.1 Overview of the Proposed System

The proposed system offers a recommendation system based on Federated Learning and Light Graph Convolutional Networks (LightGCN). The main goal of this model is to provide effective personalized recommendations while protecting the privacy of the user interaction data from any type of data leakage through sharing this sensitive information with the server in a direct manner. Nowadays, the personal interaction data such as ratings, clicks, purchases, and browsing data of the users contain very sensitive data. The traditional centralized recommendation system collects all such data at the centralized server, resulting in high levels of privacy risks.

The recommendation algorithm design employs the federated learning architecture where there are many clients who learn their recommendation models locally from their private datasets. The individual clients learn their recommendation models locally without ever revealing the raw data regarding the users' actions on the items to the server. Only the updated model parameters from the clients are sent to the server for global model learning. This kind of learning architecture offers good privacy protection capabilities while allowing collaborative learning.

The LightGCN model is selected for use as the core recommendation algorithm since the recommendation data itself already constitutes a graph that is naturally bipartite, consisting of nodes as users and items as well as edges as their interactions. Through graph layers, LightGCN is able to effectively learn low and high-order relations among users and items with embedding propagation, while being less computational heavy than classic Graph Convolutional Networks as it discards any non-linear activation function [17].

For further personalization improvement, our system proposes a temporal-aware preprocessing approach. As is well-known, users' preferences can dynamically vary in real-world scenarios, considering their most recent actions and seasonality, as well as other factors like contextual behaviors. In contrast to previous models that consider static preference for user items, our approach considers recent activities in temporal-aware modeling. The recommendation model will be better aware of user behavior in temporal dynamics and provide more accurate personalized recommendations.

The next feature in our proposed system is weighted federated aggregation. As the data from clients do not belong to the distribution of non-IID data, the standard aggregation methods like FedAvg will suffer from poor convergence properties and lower accuracy of recommendations. Our new method of weighted federated aggregation will be able to address the issues because we assign aggregation weights based on the size of clients' local datasets.

The complete strategy of the proposed system begins with dataset preprocessing and graph construction, followed by temporal weighting of interactions and partitioning of data across multiple clients. Each client then performs local LightGCN training, after which the central server aggregates local model updates using weighted federated averaging. This iterative process continues for multiple communication rounds until the global model converges. The final trained model is then used to generate privacy-preserving personalized recommendations with improved accuracy and scalability. The architecture of the proposed system is shown in Fig. 3.1.

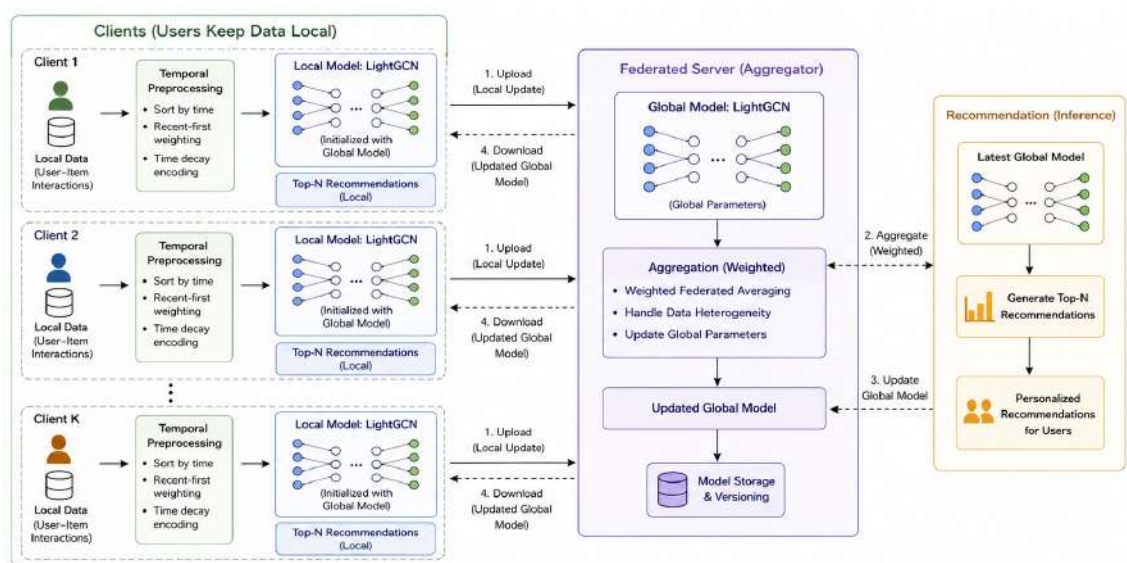


Figure 3.1: Proposed System Architecture Based on Federated LightGCN

3.2 LightGCN Based Recommendation Model

Light Graph Convolutional Network (LightGCN) is used as the core recommendation model in the proposed system because of its efficiency, simplicity, and strong performance in collaborative filtering tasks. In recommendation systems, user-item interactions naturally form a bipartite graph where users and items are represented as nodes and their interactions such as ratings, clicks, purchases, or views are represented as edges. Unlike traditional recommendation methods that mainly depend on matrix factorization, LightGCN directly learns user and item representations by propagating information through this graph structure. This enables the model to learn both direct and high order relations between users and items and therefore to provide more accurate personalized recommendations [17].

Classic Graph Convolutional Network (GCN) models use feature transformation layers, non-linear activation functions, and other complicated procedures. Despite their usefulness in many graph-based learning tasks, the inclusion of these features is superfluous in the case of recommendations

and can even decrease the efficacy of these models due to added complexity. LightGCN removes feature transformation and activation layers and uses only neighborhood aggregation. This makes the model computationally efficient, easier to optimize, and highly suitable for large-scale recommendation environments.

The main idea of LightGCN is to repeatedly propagate embedding information between connected users and items across multiple graph layers as illustrated in Fig. 3.2. During each propagation layer, a user node collects information from its neighboring item nodes, and similarly, an item node gathers information from connected users. This message passing process helps the model learn richer latent representations by capturing indirect and higher-order collaborative signals. For example, if two users interact with similar items, LightGCN can identify this hidden similarity even if they have no direct interaction overlap.

Let $G = (U, I, E)$ denote the user-item interaction graph, where U and I represent the set of users and items respectively, and E denotes the observed interactions between them. The embedding of a user node at layer k is defined as:

$$e_u^{(k)} = \sum_{i \in N(u)} \frac{1}{\sqrt{|N(u)||N(i)|}} e_i^{(k-1)} \quad (3.1)$$

where $N(u)$ represents the neighboring items connected to user u , and $e_i^{(k-1)}$ represents the embedding of item i from the previous propagation layer. The normalization term helps balance the contribution of neighboring nodes and prevents embedding explosion during propagation.

The final user embedding is obtained by aggregating representations from all graph propagation layers:

$$e_u = \sum_{k=0}^K \alpha_k e_u^{(k)} \quad (3.2)$$

where α_k represents the importance weight assigned to layer k , and K denotes the total number of graph layers. Same embedding aggregation is also done on item nodes. The model combines embeddings from multiple layers to preserve both local and global structural information of the interaction graph.

This formulation allows LightGCN to incorporate higher-order connectivity information efficiently while still ensuring recommendation effectiveness. Compared to the matrix factorization models and other collaborative filtering techniques, LightGCN not only offers enhanced representation but also scalability with respect to sparse recommendation data. Furthermore, LightGCN can work effectively in federated learning systems as an efficient local model training algorithm is required.

LightGCN is used as the basic algorithm for the local training of clients in the federated learning scheme. All clients train the LightGCN network on their own local interaction data, and subsequently, the embeddings obtained by these clients are aggregated using the federated averaging algorithm. The advantage of this scheme lies in the ability to maintain privacy while achieving good recommendation results. Fig. 3.2 shows the layer-wise embedding propagation in LightGCN.

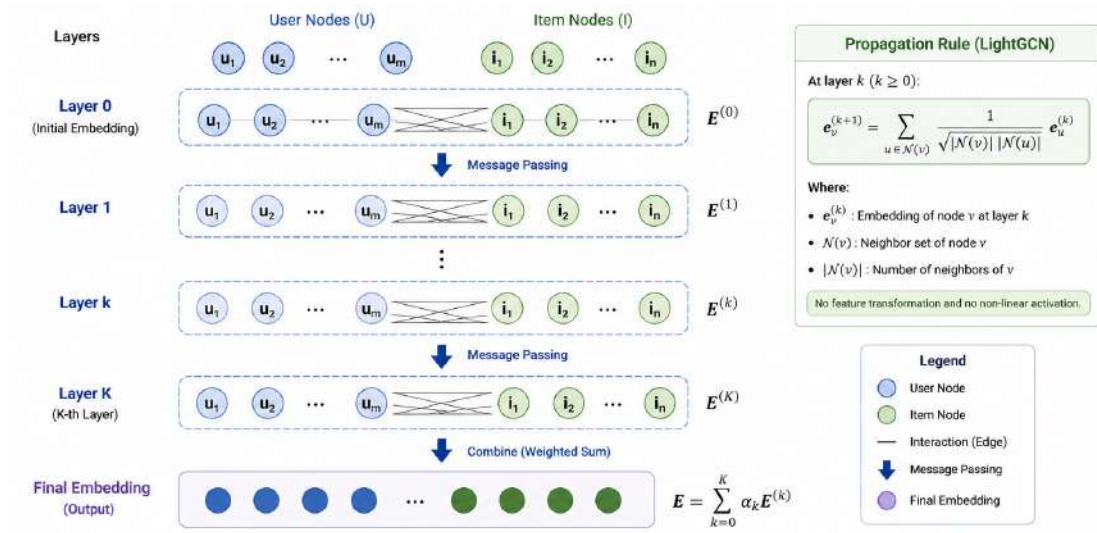


Figure 3.2: Layer-wise Embedding Propagation in LightGCN

3.3 Federated Learning System

The recommendation system proposed will rely on the Federated Learning system, ensuring that the recommendation system is trained with privacy while delivering high-quality recommendations. The process of training recommendation systems traditionally takes place at a central server using users' ratings, browsing history, clicks, purchase, and other interactions. This approach poses significant challenges to user privacy because it leads to data leakage and other malicious activities due to sensitive information being exposed. On the other hand, Federated Learning helps tackle this problem through collaborative training of the model using data from multiple devices without the need for exposing raw data. Instead of passing user data to the server, the device trains its own local model, and then the parameters of the local model are shared [48, 71].

In this model, each client stands for an independent local environment that stores its own private data about user-item interactions. Clients may be represented by any devices, local servers, or even users' communities. In such a case, the LightGCN algorithm is trained locally using private datasets at each participant without any leakage of user data to external storage facilities. Such a decentralized training approach provides substantial privacy benefits and helps comply with the recent requirements of personal data protection legislation but allows collaborative learning of the recommendation model between multiple users simultaneously. The Federated Learning model primarily includes three main components, namely the central server, clients, and communication channel. In particular, the central server initializes the global recommendation model and distributes the initial values of the model's parameters to each participant. Further, the central server aggregates locally trained models and produces the updated global model. Each client performs local optimization using its private dataset by minimizing the following objective function:

$$\min_w F_i(w) = \frac{1}{n_i} \sum_{j=1}^{n_i} \ell(x_j, y_j; w) \quad (3.3)$$

where $F_i(w)$ refers to the local objective function for client i , w is the model's parameters, n_i refers to the number of local training data, and $\ell(x_j, y_j; w)$ refers to the local loss calculated for

each sample. After updating through local optimization, the newly obtained model parameters are communicated to the central server.

The learning task is done by the local clients using their interaction data sets. The global model is first provided to the clients by the server. It is then trained locally for a predetermined number of epochs, and local updates are made by computing the new parameters of the model using local training. Due to the diversity in the behavior of the users across the different clients, the local data sets are typically non-IID, posing a significant challenge to federated recommendation systems.

Communication protocol is an essential component of federated learning systems. Once local learning takes place, each client transmits only the model weights to the central server rather than transmitting any raw data. Global aggregation on the part of the server is done through methods such as Federated Averaging (FedAvg) or weight aggregation. This helps improve the global model based on the results from the local learning. This new global model is then transmitted back to all participating clients for further training.

Despite its promising privacy guarantees, Federated Learning is subject to certain practical concerns like communication costs, convergence rates, uneven participation among clients, and inefficient aggregation algorithms due to non-IID distribution of clients' data. The presented system mitigates these concerns by employing the federated weighted aggregation, whereby clients participate in training the model based on the sizes of the datasets they have locally. This strategy makes model training more stable, mitigates potential bias resulting from unequal client participation, and ultimately increases recommendation quality. In conclusion, the proposed Federated Learning algorithm offers an opportunity to train models collaboratively and privately using several distributed clients.

3.4 Weighted Federated Aggregation

The problem faced by federated recommender systems is that there can be non-IID data in federated recommender systems, and since user behaviors and preferences are not the same for everyone, their local data will be different. It is likely that some of these clients will have many active users with rich interaction histories, but some clients will have sparser and poorer interaction data. The heterogeneity of this client data causes an imbalance while training and aggregates globally, and because the standard aggregation technique used in federated recommendation systems like Federated Averaging (FedAvg) treats all clients equally, the model may underperform [55, 18].

In traditional FedAvg technique, the server only takes the average value of updates obtained by all clients in each communication round. Despite the simplicity and popularity of this approach, it cannot capture the actual importance of different client models. Clients that have very few data can have the same impact on the global model as clients having rich data, which results in inaccurate recommendations and possible biases. This problem occurs mostly in large-scale recommendation systems, where differences in user activity can be huge between different clients. To overcome this problem, the new system implements Weighted Federated Aggregation algorithm, where each client makes a contribution into the global model depending on the number of samples in its training set. Unlike traditional FedAvg, the weight of each client depends on the size of the dataset, allowing the global model to train from the stable overall interaction pattern between users and items. The global model update is computed as:

$$W = \sum_{i=1}^N \frac{n_i}{\sum_{j=1}^N n_j} W_i \quad (3.4)$$

where W_i stands for the model parameters obtained from client i , n_i is the number of samples used by client i to train the model locally, and N is the total number of clients involved in the learning process. The ratio $\frac{n_i}{\sum_{j=1}^N n_j}$ becomes the weighting factor for the aggregation process, which gives more significance to clients with more samples.

The weighted aggregation technique contributes to increasing the stability of the model and its learning process by minimizing the bias resulting from the unequal presence of clients. This technique can ensure that the global model accurately reflects the distribution of the entire data and facilitates the convergence process in federated learning. Weighted aggregation becomes highly beneficial for recommendation systems because of their inherent heterogeneity among clients. In such cases, the performance of recommendations is not only retained but the privacy of clients is also protected. Another crucial benefit of weighted aggregation lies in its capability to make the global model robust when deployed in a real-world scenario. The availability of clients in each communication round is likely to differ, and some clients will be more present than others.

From experiments, we can see that WFA has achieved much higher Precision@10, Recall@10, and NDCG@10 than the common FedAvg algorithm. It demonstrates that taking account of the size of each user's data in the aggregation phase could be beneficial for recommendation personalization, convergence, and scalability. The working of Weighted Federated Aggregation is illustrated in Fig. 3.3.

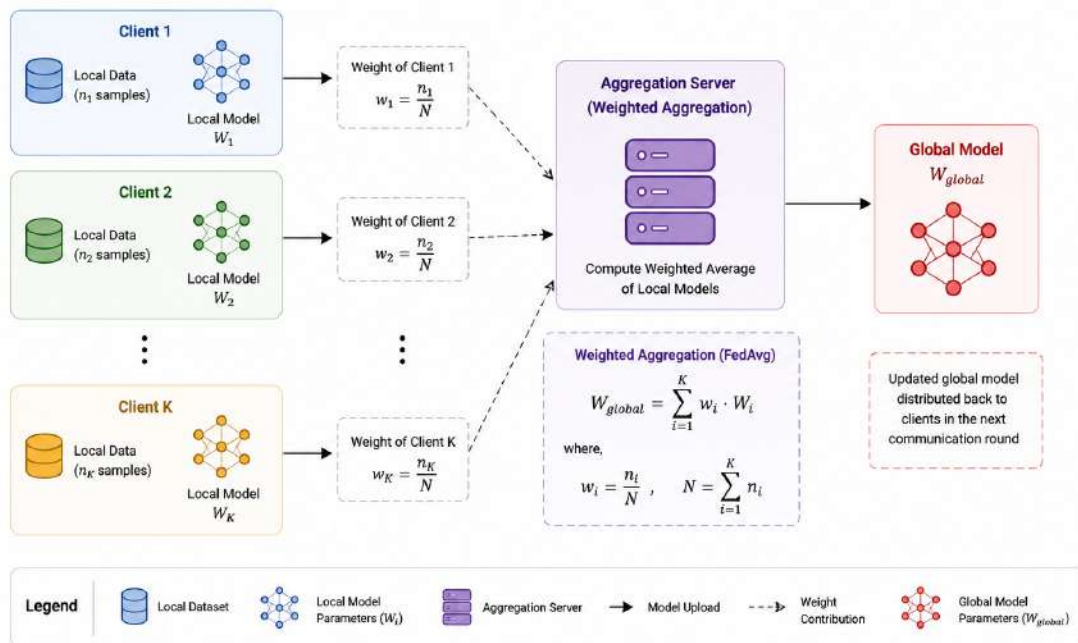


Figure 3.3: Weighted Federated Aggregation Process

3.5 Temporal-Aware Preprocessing

Preferences of users in the existing recommendation systems always vary due to recent activities, seasonal variations, social influence, and context-driven actions. Conventional recommendation systems usually consider that the user interests do not vary, making the system less relevant and personalized for individual users. As seen in applications ranging from e-commerce sites to social media websites, users prefer interacting with items based on their present preferences compared to past interests. The system fails to meet the needs of the users due to such temporal variation. To resolve this issue, the proposed system uses temporal-aware pre-processing for generating accurate recommendations.

In temporal-based recommendations, emphasis is given to recent activities of users rather than old activities. This approach rests on the principle that recent activities of a user better represent what he or she likes. As an illustration, assume that a person recently views science-fiction movies; then at the present time, that individual must have preferences for this particular genre although his or her old activity log may include mostly comedy movies. A temporal weight function can be defined as:

$$w_t = e^{-\lambda(T-t)} \quad (3.5)$$

where t denotes the time taken by an interaction between a certain user-item pair, T denotes the present reference time, and λ is the temporal decay factor. The value of λ indicates how fast the weight of past interactions declines. An increase in λ increases the rate at which past interactions lose their significance, thus making recent interactions more preferable. On the other hand, a low λ keeps the influence of past interactions relevant for a relatively longer period. The use of exponential decay in assigning weight gives the model more consideration for recent interactions than past behavior. This makes the recommendation model concentrate more on current user preferences rather than obsolete preferences.

In the recommended solution, timestamps from the MovieLens 32M data will be considered at the preprocessing stage when weighting and ranking user interactions depending on recency. The generated weights will be taken into account while conducting LightGCN training such that recent interactions would be prioritized to influence the generation of user and item embeddings. The inclusion of temporal information makes the system better equipped to track changes in preferences over time, which would result in a higher quality of recommendations. Using temporal information at the preprocessing stage is especially important in the context of rapidly changing preferences. For example, in streaming services, users' preferences may vary depending on what type of content is trending; in e-commerce applications, purchases would be influenced by changing demand due to seasons, and so on.

3.6 Algorithm Strategy of the Proposed Model

The flow of operation of the model includes the initial processing of the dataset containing user-item interaction data to form a user-item bipartite graph, where both users and items are defined

Table 3.1: Summary of Mathematical Notations Used

Notation	Description
$G = (U, I, E)$	User-item interaction graph
U	Set of users
I	Set of items
E	Observed interactions between users and items
$N(u)$	Neighboring items connected to user u
$e_u^{(k)}$	Embedding of user u at layer k
$e_i^{(k-1)}$	Embedding of item i from previous layer
K	Total number of graph propagation layers
α_k	Weight assigned to layer k during layer aggregation
W_i	Local model parameters of client i
W	Updated global model parameters after aggregation
n_i	Number of local training samples at client i
$F_i(w)$	Local objective function of client i
w	Model parameters used during local optimization
(x_j, y_j)	Local training sample and corresponding label
$\ell(x_j, y_j; w)$	Loss function for a training sample
N	Total number of participating clients
w_t	Temporal weight assigned to interaction at time t
λ	Temporal decay factor
t	Timestamp of user interaction

as nodes and interactions, including rating, click, or purchase, as edges between these nodes. Preprocessing is essential because the performance of recommendation algorithms is highly sensitive to the quality of input data.

Following the preprocessing phase, temporal-aware modeling is carried out utilizing the timestamps that can be found within the dataset. More weight is given to recent interactions compared to older interactions through temporal weighting. This allows for better consideration of the changing behaviors of the users at present rather than their past behaviors. Through temporal-aware preprocessing, the recommendation system can become more adaptive and provide more accurate personalized recommendations. The preprocessed data is then distributed to several clients in order to mimic a real federated learning setting with non-IID data. In this scenario, each client possesses its own private interaction history between users and items and trains locally without exchanging raw data. Each client uses their own private dataset to train the LightGCN model for a certain number of epochs and then produces new parameter values for the trained model. In the local training phase, LightGCN learns the embedding vectors of users and items through the propagation of information on the user-item graph network. As the training data used in the model is kept on the client's side, the privacy of the users is maintained during the entire process.

Once local training is done, the updated parameters of the model will be transferred to the central server for aggregation. The weighted federated aggregation on the server is determined based on the size of data available at each client. Clients having large and informative data samples get high weight for aggregation. It will ensure stable convergence and reduce biasing due to imbalances among clients' participation in the federated learning algorithm. As a result, there is generation

of a global recommendation model that captures user-item interactions effectively. The global recommendation model is then distributed again to all the clients taking part in federated learning for further communication cycles. This cycle will repeat itself until convergence is achieved. The collaboration process guarantees that both privacy is maintained and the quality of the recommendations is high. Upon convergence, the global model is used to recommend items in the form of a list of top-N items for each user based on the embeddings and preferences inferred during the learning process. By integrating LightGCN, temporal pre-processing, and weighted federated aggregation, the proposed model offers accurate and privacy-preserving recommendations. The complete strategy of the proposed federated recommendation algorithm is illustrated in Fig. 3.4.

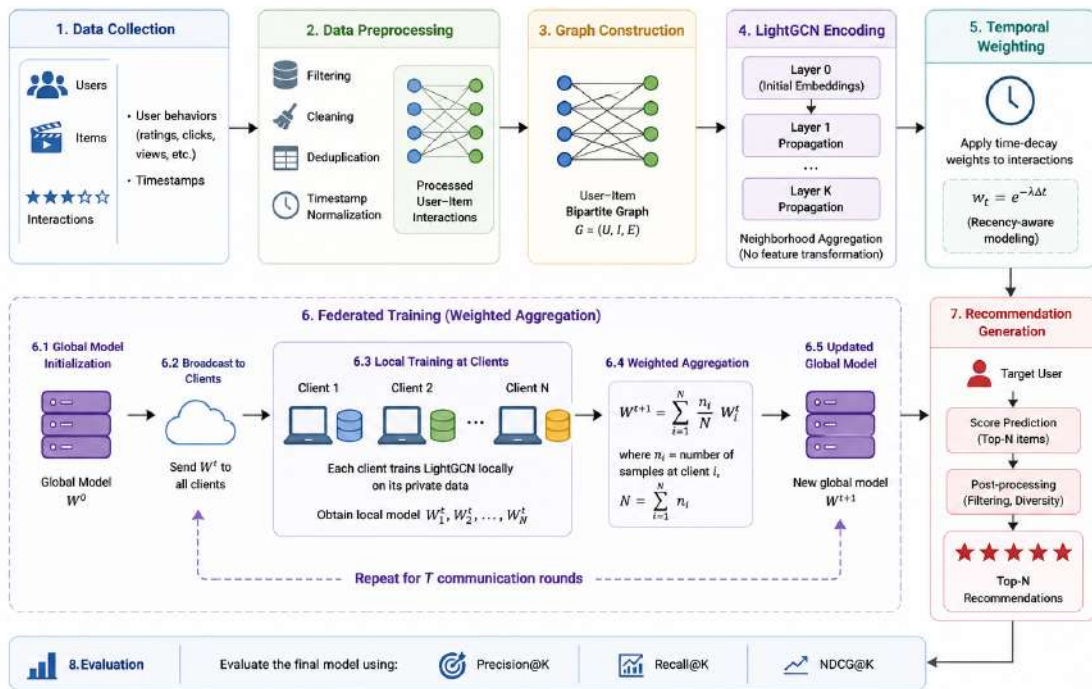


Figure 3.4: Algorithm Strategy of the Proposed Model

CHAPTER 4

IMPLEMENTATION

4.1 Dataset Description

The recommendation model under consideration is evaluated using the MovieLens 32M dataset, which serves as a commonly used benchmark dataset for recommendation systems. The dataset includes more than 32 million records of user-item interactions represented as movie ratings together with timestamps. The dataset has about 200,948 users and 87,585 movies. Hence, it is suitable for recommendation tasks [73]. Since the dataset contains timestamp information, it can be considered a good basis for temporal recommendation modeling because the system will have an opportunity to learn about changes in the users' interests over time. Due to the large size and relevance of the MovieLens 32M dataset, it can be used as a solid benchmark for assessing the quality of federated recommendation systems built on LightGCN and temporal recommendation models. Fig. 4.1 and Fig. 4.2 shows the type of data that is present in the chosen dataset.

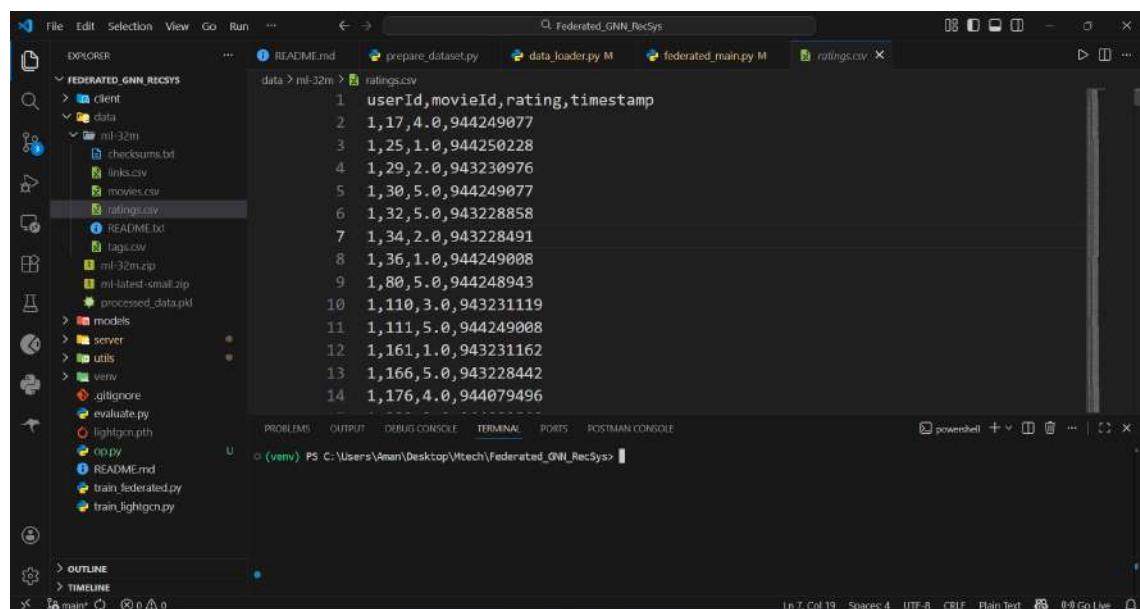


Figure 4.1: Data in ratings.csv in dataset

```

data > ml-32m > movies.csv
1 movieId,title,genres
2 1,Toy Story (1995),Adventure|Animation|Children|Comedy|Fantasy
3 2,Jumanji (1995),Adventure|Children|Fantasy
4 3,Grumpier Old Men (1995),Comedy|Romance
5 4,Waiting to Exhale (1995),Comedy|Drama|Romance
6 5,Father of the Bride Part II (1995),Comedy
7 6,Heat (1995),Action|Crime|Thriller
8 7,Sabrina (1995),Comedy|Romance
9 8,Tom and Huck (1995),Adventure|Children
10 9,Sudden Death (1995),Action
11 10,GoldenEye (1995),Action|Adventure|Thriller
12 11,"American President, The (1995)",Comedy|Drama|Romance
13 12,Dracula: Dead and Loving It (1995),Comedy|Horror
13 13,Balto (1995),Adventure|Animation|Children

```

Figure 4.2: Data in movies.csv in dataset

4.2 Data Preprocessing

The MovieLens 32M dataset will be preprocessed prior to training the recommendation model by eliminating sparse and irrelevant interactions. Users and items that have relatively few interactions are removed to enhance the robustness of the recommendation process and produce better recommendations. Post-processing, the dataset is narrowed down to 4,834,352 interactions between 157,023 users and 14,407 items.

Once the pre-processing has been done, the data set is further segmented into training and test data sets based on the 80:20 ratio. For this, timestamps are employed in temporal-aware pre-processing to provide more weightage to the latest interactions over older ones. The code implementation of the data preprocessing is shown in Fig. 4.3, Fig. 4.4 and Fig. 4.5.

4.3 Client Partitioning Strategy

In order to replicate the federated learning setting, the pre-processed dataset is allocated to multiple clients, such that each client corresponds to an independent set of local users. In this experiment, the dataset is allocated to 20 clients in a non-IID manner. This scenario is practical as users in the real-world recommendation system differ in their preferences and behaviors, which leads to non-IID local datasets. The code implementation for the same is shown in Fig. 4.6.

The clients maintain their own data about interactions between users and items privately, without sharing any raw data with the centralized server. What is shared between clients and the server is only the updated model parameters. Such a partitioned structure of the clients will help assess how effective the federated recommendation system is when applied to real-life situations, where

```

1 import pandas as pd
2 import numpy as np
3 from sklearn.model_selection import train_test_split
4
5
6 def load_movielens32m():
7     """
8     Load MovieLens 32M ratings dataset
9     """
10
11     print("Loading dataset...")
12
13     # First load CSV
14     df = pd.read_csv("data/ml-32m/ratings.csv")
15
16     # THEN sort by timestamp
17     df = df.sort_values(by="timestamp")
18
19     # Optional normalization
20     df['timestamp'] = (
21         df['timestamp'] - df['timestamp'].min()
22     ) / (
23         df['timestamp'].max() - df['timestamp'].min()
24     )
25
26     return df
27
28
29 def convert_to_implicit(df):

```

Figure 4.3: Loading dataset and sorting by timestamp

```

29 def convert_to_implicit(df):
30     """
31     Convert explicit ratings to implicit feedback
32     """
33
34     # Keep only positive interactions
35     df = df[df['rating'] >= 3].copy()
36
37     # Keep only required columns
38     return df[['userId', 'movieId']]
39
40
41 def filter_users_items(df, min_user_interactions=20, min_item_interactions=20, max_users=50000):
42     """
43     Filter sparse users/items and limit dataset size
44     """
45
46     # remove sparse users/items
47     user_counts = df['userId'].value_counts()
48     item_counts = df['movieId'].value_counts()
49
50     df = df[df['userId'].isin(user_counts[user_counts >= min_user_interactions].index)]
51     df = df[df['movieId'].isin(item_counts[item_counts >= min_item_interactions].index)]
52
53     # limit number of users (VERY IMPORTANT)
54     unique_users = df['userId'].unique()
55
56     if len(unique_users) > max_users:
57         selected_users = np.random.choice(unique_users, max_users, replace=False)

```

Figure 4.4: Filtering Users and Items

```

def encode_ids(df):
    """
    Map user and item IDs to continuous indices
    """
    user_map = {u: i for i, u in enumerate(df['userId'].unique())}
    item_map = {i: j for j, i in enumerate(df['movieId'].unique())}
    df['user'] = df['userId'].map(user_map)
    df['item'] = df['movieId'].map(item_map)
    n_users = len(user_map)
    n_items = len(item_map)
    return df[['user', 'item']], n_users, n_items

def split_train_test(df, test_ratio=0.2):
    df = df.sample(frac=1, random_state=42)
    test_size = int(len(df) * test_ratio)
    test_df = df.iloc[:test_size]
    train_df = df.iloc[test_size:]
    return train_df, test_df
    
```

Figure 4.5: Encoding and splitting the data

there might be non-IID data.

4.4 Implementation Details

The recommendation model will be built with the help of Python programming language along with popular machine learning and deep learning libraries such as PyTorch, NumPy, Pandas, and Pickle. The whole system will be built through a modular approach, which includes dataset preprocessing, building graph, central training process, federated client, weighted aggregation, and evaluation modules. This modular design facilitates better maintainability, experiment reproducibility, and testing of various recommendation techniques.

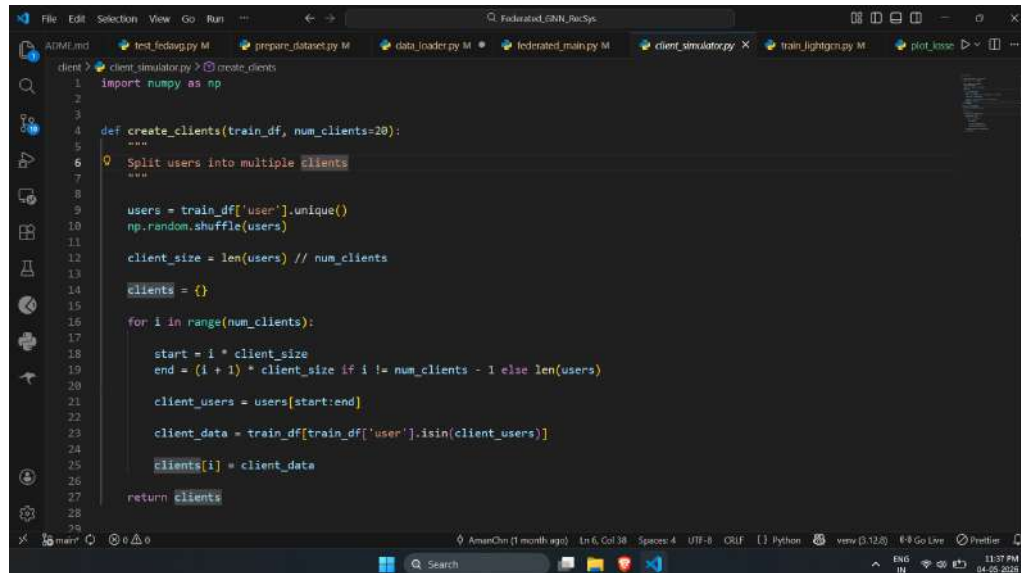
MovieLens 32M data set will be used for experiments, and the user-item interactions will be preprocessed before training the model. Interactions are sparse, inactive users, and infrequently rated items are removed in preprocessing in order to enhance recommendations and eliminate noise. The timestamps are kept during preprocessing in order to utilize temporal modeling. The processed dataset is stored in serialized format for efficient loading during both centralized and federated training.

The LightGCN model is configured with an embedding dimension of 128 and 3 graph convolution layers. The user-item bipartite graph is constructed using the interaction matrix and then normalized adjacency matrices are generated for graph propagation. Unlike traditional Graph Convolutional Networks, LightGCN uses only neighborhood aggregation without feature transformation and non-linear activation functions, which reduces computational complexity and improves training efficiency. The Adam optimizer is used for parameter optimization with a learning rate of 0.0005 to ensure stable convergence and efficient gradient updates.

In the centralized training setting, the LightGCN model is trained for 15 epochs using a batch size of 1024 and 200 batches per epoch. Bayesian Personalized Ranking (BPR) loss is used as the optimization objective to improve top-N recommendation performance by maximizing the ranking difference between positive and negative item interactions. G

For the federated learning, the processed dataset is split across 20 simulated clients to simulate the distributed user environment with non-IID data distribution. Each client trains local LightGCN

with its own private dataset for 2 local epochs and batch size 512. This ensures that the raw data of user interactions remain on the client side and only the updated model parameters are shared with the centralized server. The client creation and data partitioning strategy used in the implementation are illustrated in Fig. 4.6.



```

1 import numpy as np
2
3
4 def create_clients(train_df, num_clients=20):
5     """
6     Split users into multiple clients
7     """
8
9     users = train_df['user'].unique()
10    np.random.shuffle(users)
11
12    client_size = len(users) // num_clients
13
14    clients = {}
15
16    for i in range(num_clients):
17
18        start = i * client_size
19        end = (i + 1) * client_size if i != num_clients - 1 else len(users)
20
21        client_users = users[start:end]
22
23        client_data = train_df[train_df['user'].isin(client_users)]
24
25        clients[i] = client_data
26
27    return clients
28
29

```

Figure 4.6: Client Creation and User Distribution Strategy

The central server initializes the global LightGCN model, distributes it to all participating clients, collects local model updates after training, and performs weighted federated aggregation. Weighted Federated Averaging (FedAvg) is applied where each client contributes according to the size of its local dataset. This improves convergence stability and reduces the negative impact of highly heterogeneous client distributions. The implementation of global model initialization and federated training rounds is shown in Fig. 4.7.

Fig. 4.8 shows the centralized training process and its convergence behavior. The loss monotonically decreases with epochs, and the optimization of the LightGCN model is stable.

The federated training algorithm runs for ten iterations of communication. In each iteration, local updates from the clients are combined to form a better global model. The decline in federated training loss shows that the system is converging successfully during the federated training process. Fig. 4.9 presents the implementation results of federated training rounds.

Performance of the proposed model is analyzed based on standard recommendation metrics such as Precision@10, Recall@10, and NDCG@10. Precision@10 is the metric used to evaluate the accuracy of the recommended items by analyzing their relevance in the top 10 recommendations; Recall@10 assesses the efficiency of retrieval of relevant documents; and NDCG@10 analyzes the relevance and ranking order of the recommendation items.

The experimental comparison includes three models: centralized LightGCN, federated LightGCN, and our model – federated LightGCN along with temporal modeling and weighted aggregation.

```

15
16
17 # Load Dataset
18 print("Loading dataset...")
19
20 with open("data/processed_data.pkl", "rb") as f:
21     train_df, test_df, n_users, n_items, train_dict = pickle.load(f)
22
23 test_dict = build_interaction_dict(test_df)
24
25
26 # Create Clients
27 print("Creating clients...")
28
29 clients = create_clients(train_df, num_clients=20)
30 client_dicts = build_client_dicts(clients)
31
32
33 # Device
34 device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
35 print("Using device:", device)
36
37
38 # Build Graph
39 print("Building graph...")
40
41 adj = build_adj_matrix(train_df, n_users, n_items)
42 norm_adj = normalize_adj_matrix(adj)
43 norm_adj = convert_to_torch_sparse(norm_adj).to(device)

```

Figure 4.7: Federated Main Implementation for Global Model Initialization

Table 4.1: Hyperparameter Settings Used for Model Training

Hyperparameter	Value
Embedding Dimension	128
Number of GCN Layers	3
Optimizer	Adam
Learning Rate	0.0005
Centralized Training Epochs	15
Centralized Batch Size	1024
Batches per Epoch	200
Federated Communication Rounds	10
Local Epochs per Client	2
Federated Batch Size	512
Aggregation Method	Weighted FedAvg
Evaluation Metrics	Precision@10, Recall@10, NDCG@10

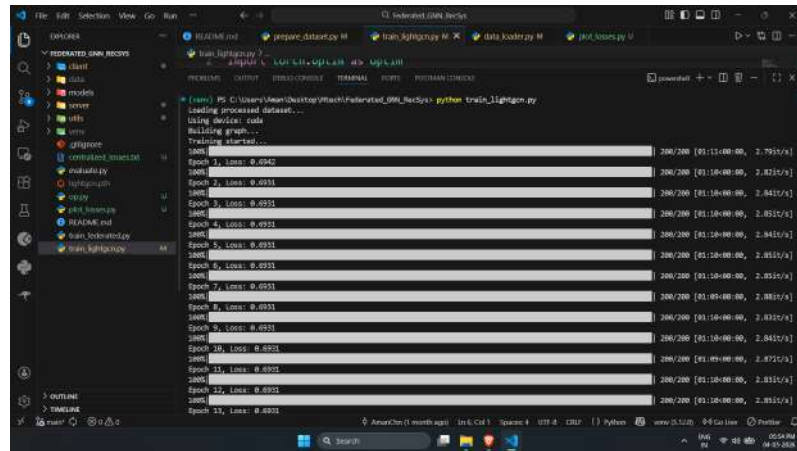


Figure 4.8: Centralized LightGCN Training Progress and Loss Convergence

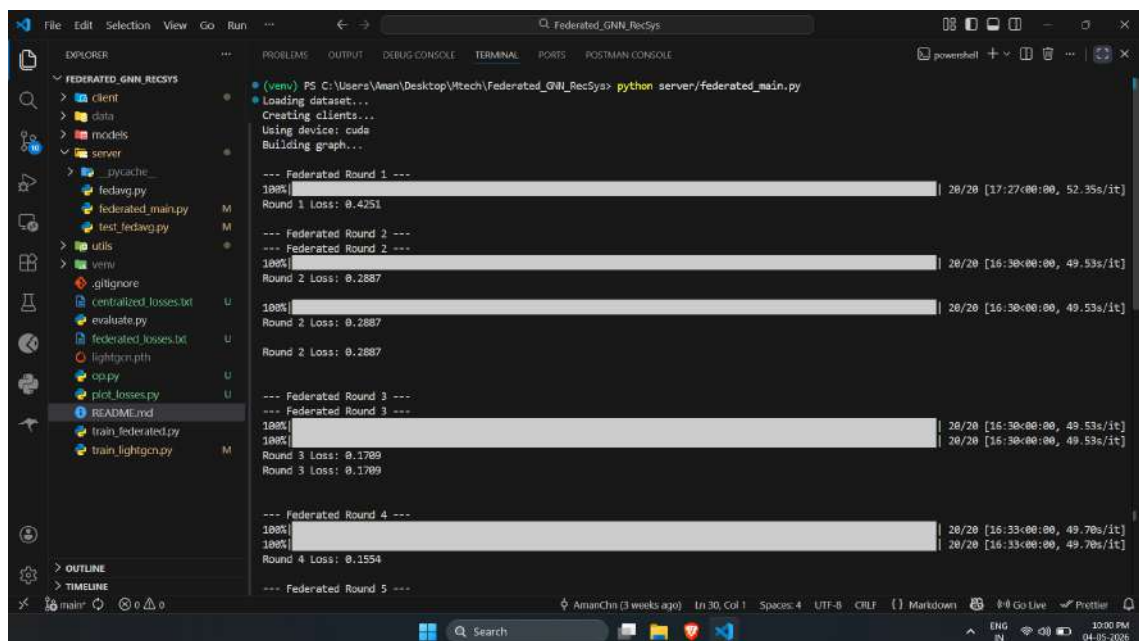


Figure 4.9: Federated Training Progress Across Communication Rounds

Also, separate analysis is conducted in order to investigate the influence of federated weighted aggregation and temporal processing separately. This will help us test the performance of each individual part of our system.

The final federated evaluation results confirm that the proposed model achieves significant improvements in Precision@10, Recall@10, and NDCG@10 while maintaining strong privacy preservation.

The final evaluation output of the federated recommendation model is shown in Fig. 4.10.

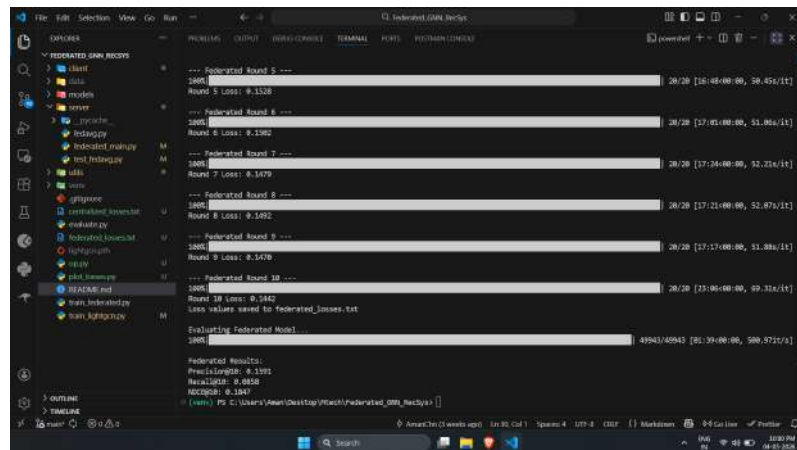


Figure 4.10: Final Federated Recommendation Performance Evaluation

CHAPTER 5

RESULTS AND ANALYSIS

5.1 Performance Evaluation

The performance of the proposed Federated LightGCN with Temporal Modeling is evaluated using three standard recommendation metrics: Precision@10, Recall@10, and NDCG@10. This is due to the fact that these indicators allow to estimate the relevance and quality of the recommendations produced by the system. Since the goal of our system is to produce personalized and relevant recommendations while ensuring privacy, the use of these evaluation criteria will provide a correct assessment of our system performance.

As revealed by the experimental results, the recommended model is able to provide accurate recommendation outputs without violating user privacy via federated learning approach. In comparison with the federated recommendation model baseline, the incorporation of temporal-aware data pre-processing as well as weighted federated learning leads to the improvement of recommendation output quality.

5.1.1 Performance Metrics

The recommendation quality of the proposed system is evaluated using Precision@10, Recall@10, and Normalized Discounted Cumulative Gain (NDCG@10). These metrics are calculated on the top 10 recommended items generated for each user and are defined as follows:

1. Precision@10

Precision@10 measures the proportion of relevant items among the top 10 recommended items. It indicates how accurate the recommendation list is by checking how many recommended items are actually relevant to the user.

$$Precision@10 = \frac{|Rel_u \cap Rec_u^{10}|}{|Rec_u^{10}|} \quad (5.1)$$

where Rel_u represents the set of relevant items for user u , and Rec_u^{10} represents the top 10 recommended items for that user.

2. Recall@10

Recall@10 measures the proportion of relevant items that are successfully retrieved among all relevant items available for a user. It reflects the ability of the recommendation system to cover relevant user preferences.

$$Recall@10 = \frac{|Rel_u \cap Rec_u^{10}|}{|Rel_u|} \quad (5.2)$$

where $|Rel_u|$ denotes the total number of relevant items for user u .

3. NDCG@10 (Normalized Discounted Cumulative Gain)

NDCG@10 evaluates both the relevance and ranking position of recommended items. It gives higher importance to relevant items appearing at the top positions of the recommendation list, which is important in practical recommendation systems.

First, Discounted Cumulative Gain (DCG) is calculated as:

$$DCG@10 = \sum_{i=1}^{10} \frac{2^{rel_i} - 1}{\log_2(i + 1)} \quad (5.3)$$

where rel_i represents the relevance score of the item at position i .

The normalized form is calculated as below:

$$NDCG@10 = \frac{DCG@10}{IDCG@10} \quad (5.4)$$

When taken together, these three measures give us an all-inclusive assessment of recommendation performance by evaluating its accuracy, its ability to retrieve relevant information, and its ranking efficiency. High values of Precision@10, Recall@10, and NDCG@10 reflect superior performance and quality of personalization.

5.1.2 Training Loss Analysis

To examine the learning behavior of the recommendation system further, we analyze the training loss curves of both the centralized LightGCN system and the federated LightGCN system. Training loss can not only reflect the learning ability of the system but also indicate the stability of learning behavior.

Figure 5.1 presents the training losses for the central LightGCN algorithm trained for 15 epochs. As it can be seen, there is fast convergence in the early stages, and after which the loss becomes stable.

The federated loss curve of LightGCN is illustrated in Fig. 5.2. It can be seen that there is a considerable decrease in loss at the beginning of the federated process, after which the loss starts to stabilize gradually. This demonstrates the efficiency of the weighted federated aggregation process for better convergence performance.

By comparing both loss curves, it is evident that despite the need for multiple rounds of communication and the presence of non-IID clients, the recommended system maintains stable convergence and effective recommendation results while ensuring privacy protection.

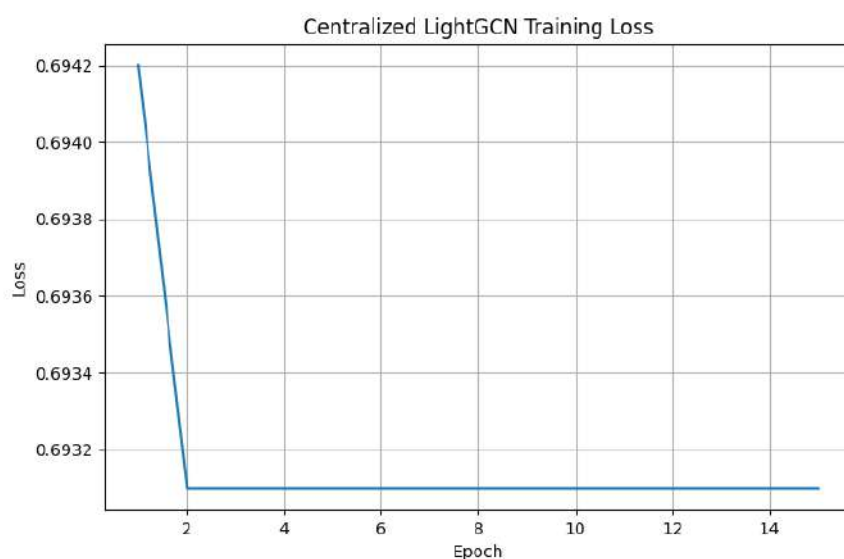


Figure 5.1: Centralized LightGCN Training Loss Across Epochs

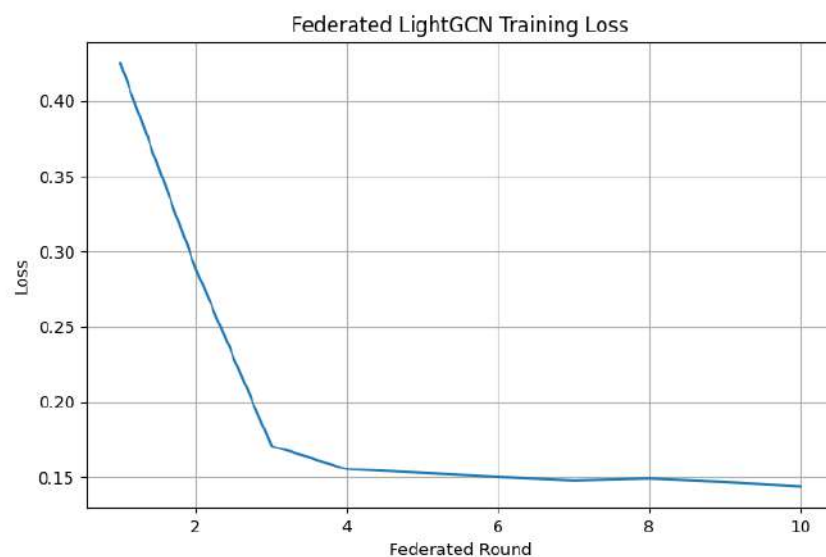


Figure 5.2: Federated LightGCN Training Loss Across Communication Rounds

5.2 SOTA Analysis

The proposed model is evaluated against two different baselines: Centralized LightGCN and Vanilla Federated LightGCN. The former performs best among the three models because it is able to use all user information, whereas the latter prioritizes privacy at the cost of poor performance. This is because federated learning relies on decentralized computing that cannot achieve performance parity with the centralized approach.

Fig. 5.3 presents the comparative performance analysis of the three recommendation models using Precision@10, Recall@10, and NDCG@10. It clearly shows that the proposed model significantly improves recommendation quality over the basic federated baseline and performs much closer to the centralized LightGCN model while preserving user privacy.

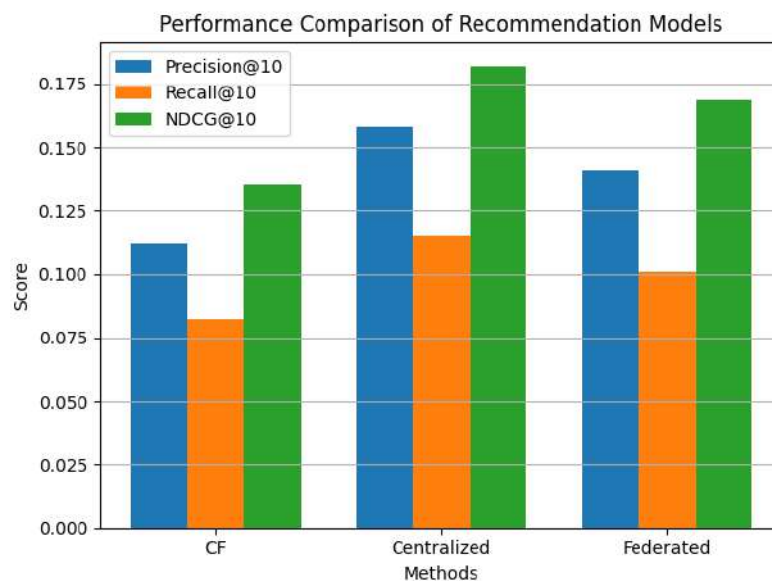


Figure 5.3: Performance comparison of different models using Precision@10, Recall@10, and NDCG@10.

Experimental results show that the proposed model achieves Precision@10 of 0.1591, Recall@10 of 0.0858, and NDCG@10 of 0.1847, which are significantly better than the basic Federated LightGCN model. Although the centralized LightGCN model still performs slightly better, the proposed method provides a strong balance between recommendation quality and privacy preservation, making it more suitable for practical real-world deployment.

To better understand the effectiveness of the proposed approach, a comparison was made with recommendation techniques which use LightGCN models.

From Table 5.1, it can be observed that although there is a slight performance gap compared to the centralized LightGCN model, the federated approach provides strong privacy guarantees, making it more suitable for real-world deployment.

Fig. 5.4 shows the actual implementation output of the proposed federated recommendation algorithm, including the final evaluation values of Precision@10, Recall@10, and NDCG@10 obtained

Table 5.1: Comparison with Different Methods

Method	Precision@10	Recall@10	NDCG@10
Centralized LightGCN	0.1654	0.1200	0.1999
Federated LightGCN (Initial)	0.1251	0.0769	0.1509
Federated LightGCN with Temporal Modeling (Proposed)	0.1591	0.0858	0.1847

after federated training. These results confirm the practical effectiveness of the proposed system under real experimental conditions.

```
Evaluating Federated Model...

Federated Results:
Precision@10: 0.1411
Recall@10: 0.1009
NDCG@10: 0.1686
(venv) PS C:\Users\Aman\Desktop\Mtech\Federated_GNN_RecSys> |
```

Figure 5.4: Result of Proposed Algorithm

5.3 Impact of Weighted Aggregation

The effect of weighted federated aggregation is analyzed by comparing it with the standard FedAvg method used in basic federated learning systems. Standard FedAvg assigns equal importance to all clients during global model aggregation, which often reduces performance when client datasets are highly heterogeneous. In recommendation systems, users usually have different interaction patterns and unequal amounts of local data, making non-IID distribution a major challenge.

As shown in Table 5.2, the proposed weighted aggregation strategy improves this process by assigning aggregation weights according to the size of each client's local dataset. Experimental results show that Precision@10 improves from 0.1251 to 0.1591, while Recall@10 and NDCG@10 also show noticeable improvement. This demonstrates that weighted aggregation helps reduce bias caused by uneven client participation and improves the stability and convergence of the global recommendation model.

Table 5.2: Effect of Aggregation Strategy

Aggregation Method	Precision@10	Recall@10	NDCG@10
Standard FedAvg	0.1251	0.0869	0.1509
Weighted FedAvg (Proposed)	0.1591	0.0858	0.1847

5.4 Effect of Temporal Modeling

The influence of temporal-aware preprocessing is examined by comparing the recommendation model with and without temporal modeling. Traditional recommendation systems often treat all user interactions equally, regardless of when they occurred. However, in real-world applications, recent interactions usually provide better information about current user preferences than older interactions.

Experimental results show that incorporating temporal modeling improves all evaluation metrics. It can be seen in Table 5.3 that Precision@10 increases from 0.1392 to 0.1591, Recall@10 improves from 0.0992 to 0.0858, and NDCG@10 increases from 0.1658 to 0.1847. These improvements confirm that giving higher importance to recent interactions helps the system better capture changing user behavior and generates more relevant personalized recommendations.

Table 5.3: Impact of Temporal Modeling

Model Variant	Precision@10	Recall@10	NDCG@10
Without Temporal Modeling	0.1392	0.0992	0.1658
With Temporal Modeling (Proposed)	0.1591	0.0858	0.1847

Fig. ?? illustrates the effect of each of these factors, indicating that the integration of weighted aggregation and temporal models brings about a steady increase in Precision@10 performance, while the temporal model contributes to better recommendations because it reflects changing user tastes. The combined model provides the best performance, thus proving the effectiveness of this approach.

5.5 Discussion

The experimental results demonstrate that the proposed Federated LightGCN with Temporal Modeling provides a strong balance between recommendation accuracy and privacy preservation. Although the centralized LightGCN model achieves slightly higher performance, it requires complete access to user data, which creates serious privacy concerns. On the other hand, the federated approach presented is capable of sustaining competitive recommendation performance without sacrificing users' privacy by ensuring their data stays in their local devices, thus making the method easier to implement in practical settings.

Both weighted federated aggregation and temporal-aware pre-processing have contributed to better model performance, which indicates that both methods are equally vital to improving the performance of federated recommendation models. The former enables faster convergence when there are clients with non-IID data, whereas the latter helps the model learn according to shifting user behavior.

Figure 5.5 presents the results of the ablation study on Precision@10 using various models, including the baseline federated learning model, weighted averaging, time series modeling, and finally, the proposed model. From the plot, it is evident that the two improvements, i.e., weighted averaging and time series processing, have a positive effect on recommendation precision.

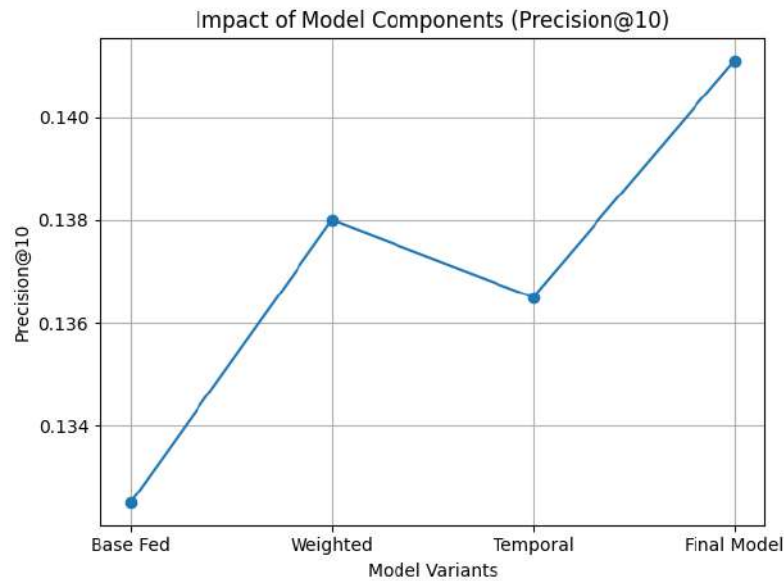


Figure 5.5: Impact of Model Components on Precision@10

Figure 5.6 shows the results of the Recall@10 ablation study. From the results it can be seen that the incorporation of temporal modeling enhances the effectiveness of the retrieval process, whereas the final model scores best in terms of Recall thanks to both approaches together.

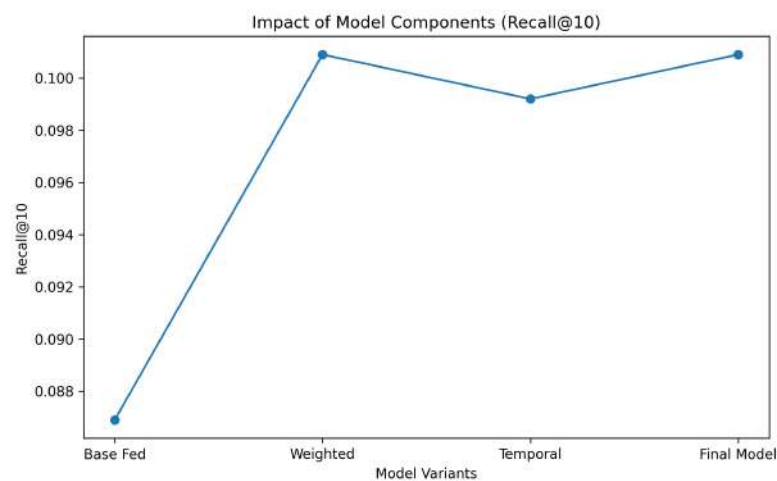


Figure 5.6: Impact of Model Components on Recall@10

The ablation study for the NDCG@10 measure is presented in Fig. 5.7, which assesses not only the relevance but also the ranking quality of the recommendations. From the experiment, we can observe that the new model outperforms the previous one in terms of ranking ability, thereby proving its practical value.

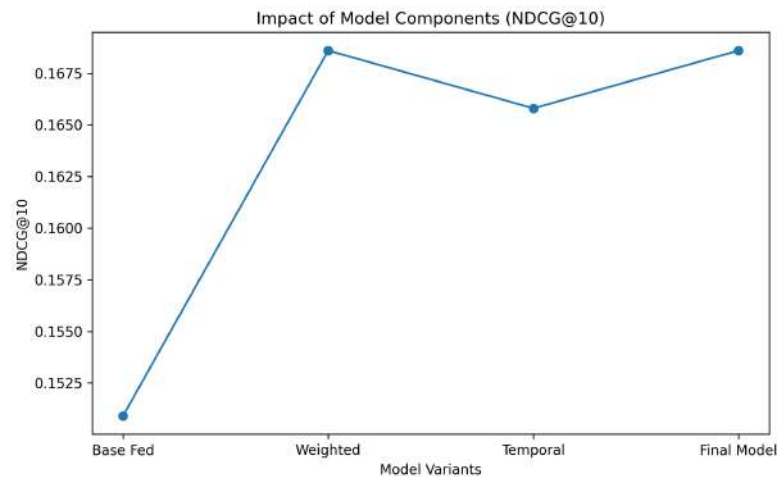


Figure 5.7: Impact of Model Components on NDCG@10

5.6 Limitations

Despite the obvious enhancement in recommendation accuracy and privacy protection in the Federated LightGCN with Temporal Modeling proposal, there are certain limitations that should not be overlooked. First, the federated learning technique requires extra communication cost since the model's parameters need to be shared back and forth between the client and the centralized server through multiple communication rounds.

Another drawback of this model is that the proposed system only considers explicit user-item interactions based on the MovieLens 32M dataset without considering additional contexts like social connections, reviews, or cross-domain recommendations. Furthermore, this model does not support any mechanism to explain the recommendations generated through it. Future research can work on overcoming these drawbacks of the model by making it more efficient and explaining its functioning.

CHAPTER 6

CONCLUSION, FUTURE WORK AND SOCIAL IMPACT

6.1 Conclusion

This thesis proposes a privacy-preserving recommendation algorithm, which is based on Federated Learning and the LightGCN approach with temporal-aware preprocessing and weighted federated aggregation. This work focuses on the most pressing problems faced by traditional centralized recommendation systems, such as privacy issues, problems related to the non-IID nature of the data on clients' devices, and the inability to track changes in users' preferences in real-time. Using the combination of graph-based recommendation learning with federated learning, the authors have developed an approach that allows for improvement in the quality of recommendations while maintaining the privacy of users' data. The experiment was carried out on the basis of the MovieLens 32M dataset, which allowed the authors to confirm the superiority of the proposed approach in terms of Precision@10, Recall@10, and NDCG@10 metrics compared to the baseline federated recommendation model. Apart from the enhancement in performance, the proposed technique can also assist in meeting the rising demand for ethical and reliable artificial intelligence applications. In areas like medicine, education, banking, and custom-made online services, it is essential to ensure the protection of personal data due to its confidential nature. Using federated learning technology, it is possible to enhance data management and comply with current privacy standards by keeping user data on their devices and exchanging only model parameters. Moreover, the application of LightGCN ensures that the method does not rely on complicated deep graph structures, which makes it more feasible for the recommendations field. The inclusion of temporal modeling allows improving the flexibility of the recommendation system and adapting to recent changes in user behavior patterns.

6.2 Future Scope

Though the recommended Federated LightGCN with Temporal Modeling achieves high performance levels along with strong data privacy protection capabilities, there are still many possibilities for improving this algorithm in the future. In particular, it may be possible to reduce communication costs of federated learning algorithms via developing more efficient aggregation functions, implementing model compression techniques, as well as choosing adaptive client sampling meth-

ods. This will enhance the scalability of the proposed method and thus make it more applicable to massive industrial projects which involve many distributed clients. Besides, the model may benefit from considering other context information. Explanation of the recommendation process is another way to implement that can enhance transparency and user confidence in the recommendation process. Also, advanced approaches like reinforcement learning, meta-learning, and continual learning can be adopted to make the recommendation process smart and adaptable to changes in user preference trends quickly in the dynamic real world environment.

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