Leveraging Deep Learning Approach for Movie Recommendation

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ABSTRACT :

Recommender systems are employed either as tools or algorithms, whose key task is to efficiently predict the ratings for items and recommend items, using the data generated by users. It assists users in finding items that they will like. Hence, recommendation systems are becoming an essential part of some applications, e-commerce websites, and online streaming services, etc. This paper emphasizes on recommendation system for movies whose main objective is to propose a movie recommendation system through a deep learning technique. The size and complication of websites have increased due to the rapid growth of the internet. On these websites, it has become time consuming and extremely difficult for the users to find the information that they are searching for. Therefore, a collaborative filtering-based movie recommendation system using deep learning and embedding is proposed. The proposed system is evaluated by calculating the RMSE and MAE values. The proposed method is compared with other machine learning

Keywords: *recommendation systems, e-commerce websites.*

I. INTRODUCTION

With the ever-growing size and complexity of online content, users often face challenges in locating content that aligns with their interests. Recommender systems have emerged as vital tools in filtering vast datasets to deliver personalized suggestions. These systems play a crucial role in domains such as e- commerce, online streaming platforms, and content-driven websites. Specifically, in the movie industry, recommendation systems help users navigate extensive libraries of films based on their preferences.

Traditional recommendation systems largely rely on collaborative filtering and content-based approaches. However, these methods often struggle with scalability, sparsity, and cold start problems. To overcome these limitations, deep learning techniques have been increasingly adopted due to their ability to capture complex patterns in large datasets.

This paper presents a deep learning-based collaborative filtering model for movie recommendations. By utilizing embedding layers for users and movies, and passing the concatenated vectors through fully connected layers with dropout and ReLU activations, the proposed system effectively learns user-movie interaction patterns. The output is a predicted rating for a given user-movie pair, scaled between 1 and 5. This approach aims to enhance recommendation accuracy and provide a more personalized user experience.

II.LITERATURE REVIEW

Sharma Sunny, Rana Vijay, Kumar Vivek. Deep learning based semantic personalized recommendation system[J]. *International Journal of Information Management Data Insights*, 2021

The past decade has seen significant development in the number of personalized recommendation applications on the World Wide Web. It aims to assist users to retrieve relevant items from a large repository of contents by providing items or services of likely interest based on examined evidence of the users' preferences and desires. However, this vision is complex due to the huge amount of information aka media-rich information available on the web. Most of the systems formulated so far use the metadata linked with the digital contents, but such systems fail to generate significant recommendations results. In these circumstances, a semantic personalized recommendation system (SPRS) plays an important role to take away the semantic gap between high-level semantic contents and low-level media features. The proposed system recommends personalized sets of videos to users depending on their previous activity on the site and exploits a domain ontology and user items content to the domain concepts. To evaluate the performance of the framework, items' prediction is executed by utilizing the proposed framework, and performance is determined by comparing the predicted and actual ratings of the items in terms of Predictive Accuracy Metrics, precision, and recall.**[1]**

Fan W, Ma Y, Li Q, et al. Graph neural networks for social recommendation[C] // The world wide web conference. 2019

In recent years, Graph Neural Networks (GNNs), which can naturally integrate node information and topological structure, have been demonstrated to be powerful in learning on graph data. These advantages of GNNs provide great potential to advance social recommendation since data in social recommender systems can be represented as user-user social graph and user-item graph; and learning latent factors of users and items is the key. However, building social recommender systems based on GNNs faces challenges. For example, the user-item graph encodes both interactions and their associated opinions; social relations have heterogeneous strengths; users involve in two graphs (e.g., the user-user social graph and the user-item graph). To address the three aforementioned challenges simultaneously, in this paper, we present a novel graph neural network framework (GraphRec) for social recommendations. In particular, we provide a principled approach to jointly capture interactions and opinions in the user-item graph and propose the framework GraphRec, which coherently models two graphs and heterogeneous strengths. Extensive experiments on two real-world datasets demonstrate the effectiveness of the proposed framework GraphRec.**[2]**

Guo Z, Wang H. A deep graph neural network-based mechanism For social recommendations[J]. *IEEE Transactions on Industrial Informatics*, 2020

Nowadays, the issue of information overload is gradually gaining exposure in the Internet of Things (IoT), calling for more research on recommender system in advance for industrial IoT scenarios. With the ever-increasing prevalence of various social networks, social recommendations (SoR) will certainly become an integral application that provides more feasibly personalized information service for future IoT users. However, almost all of the existing research managed to explore and quantify correlations between user preferences and social relationships, while neglecting the correlations among item features which could further influence the topologies of some social groups. To tackle with this challenge, in this article, a deep graph neural network-based social recommendation framework (GNN-SoR) is proposed for future IoTs. First, user and item feature spaces are abstracted as two graph networks and respectively encoded via the graph neural network method. Next, two encoded spaces are embedded into two latent factors of matrix factorization to complete missing rating values in a user- item rating matrix. Finally, a large amount of experiments are conducted on three real- world data sets to verify the efficiency and stability of the proposed GNN-SoR.**[3]**

Cami B R, Hassanpour H, Mashayekhi H. A content-based movie recommender system based on temporal user preferences[C] // 2017 3rd Iranian conference on intelligent systems and signal processing (ICSPIS). IEEE, 2017

Recommender systems have emerged as the essential part of many e-commerce web sites. These systems provide personalized services to assist users in finding favorite items among the huge number of available media on the World Wide Web. Identifying temporal preferences of individuals is one of the major challenges of recommender systems to provide personalization for users. In this paper, a content-based movie recommender system is proposed that captures the temporal user preferences in user modeling and predicts the preferred movies. The proposed method provides a user-centered framework that incorporates the content attributes of rated movies (for each user) into a Dirichlet Process Mixture Model to infer user preferences and provide a proper recommendation list. We implement the proposed method and use the MovieLens dataset to perform experiments. The evaluation results show that the performance of proposed recommendation method outperforms the existing movie recommender systems.**[4]**

Guo T, Luo J, Dong K, et al. Locally differentially private item-based collaborative filtering[J]. *Information Sciences*, 2019

Recently, item-based collaborative filtering has attracted a lot of attention. It recommends to users new items which may be of interests to them, based on their reported historical data (i.e., the items they have already been interested in). The reported historical data leads to significant privacy risks in case that the recommending service is not fully trusted. Many researches have focused on developing differential privacy mechanisms to protect personal data in various recommendations. However, most of these mechanisms can not ensure accuracy of the recommendations. The main reason for this problem is that these methods compute similarity directly from the perturbation data. The computed similarity is thus always inaccurate and this inaccurate similarity finally leads to inaccurate recommendation results. In this paper, we propose a locally differentially private item-based collaborative filtering framework, which protects users' private historical data on the user-side, and on the server-side reconstructs the similarity to ensure recommendation accuracy. The similarities are reconstructed for every pair of items, by estimating the number of users who have rated neither, either one, or both of them.**[5]**

Zhang Z, Dong M, Ota K, et al. Alleviating new user cold-start in user-based collaborative filtering via bipartite network[J]. *IEEE Transactions on Computational Social Systems*, 2020

The recommender system (RS) can help us extract valuable data from a huge amount of raw information. User-based collaborative filtering (UBCF) is widely employed in practical RSs due to its outstanding performance. However, the traditional UBCF is subject to the new user cold-start issue because a new user is often extreme lack of available rating information. In this article, we develop a novel approach that incorporates a bipartite network into UBCF for enhancing the recommendation quality of new users. First, through the statistic and analysis of new users' rating characteristics, we collect niche items and map the corresponding rating matrix to a weighted bipartite network. Furthermore, a new weighted bipartite modularity index merging normalized rating information is present to conduct the community partition that realizes coclustering of users and items.**[6]**

Nilashi M, Ibrahim O, Bagherifard K. A recommender system based on collaborative filtering using ontology and dimensionality reduction techniques[J]. *Expert Systems with Applications*,

2018

Improving the efficiency of methods has been a big challenge in recommender systems. It has been also important to consider the trade-off between the accuracy and the computation time in recommending the items by the recommender systems as they need to produce the recommendations accurately and meanwhile in real-time. In this regard, this research develops a new hybrid recommendation method based on Collaborative Filtering (CF) approaches. Accordingly, in this research we solve two main drawbacks of recommender systems, sparsity and scalability, using dimensionality reduction and ontology techniques. Then, we use ontology to improve the accuracy of recommendations in CF part. In the CF part, we also use a dimensionality reduction technique, Singular Value Decomposition (SVD), to find the most similar items and users in each cluster of items and users which can significantly improve the scalability of the recommendation method.**[7]**

Huang Z, Yu C, Ni J, et al. An efficient hybrid recommendation model with deep neural networks[J]. *IEEE Access*, 2019

Recently, deep learning has gained great popularity in the area of recommender systems. Various combinations of deep learning, collaborative recommendation and content-based recommendation have occurred. However, as one of the three most significant recommendation techniques, hybrid recommendation has little cooperation with deep learning. Besides, most current deep hybrid models only incorporate two simple recommendation methods together in post- fusion, leaving massive space for further.**[8]**

III.EXISTING SYSTEM

A recommendation system is now a central part of all ecommerce applications and online entertainment services. The recommendation system gains data about the user's preferences for a particular item (e.g. songs, movies, games,
music, etc.) in two different ways. An implicit way of obtaining user data involves observing the user's past behavior such as order history, watched movies, and search queries. Another way of obtaining data is done by gathering the user's previous ratings and likes. The size and complication of websites have increased due to the exponential growth of the internet. On these websites, it has become time- consuming and extremely difficult for the users to find the information that they are searching for. Recommendation systems assist users in finding the information that is within their interests by some interaction with the user. A Recommendation system predicts the rating for items that the user has not rated yet based on his previous ratings and ratings by similar users

3.1 DISADVANTAGES

Data Sparsity: In large systems with thousands of users and items, most users interact with only a small subset of items, leading to sparse interaction matrices. Sparse data reduces the effectiveness of collaborative filtering methods.

Scalability Issues: As the number of users and items increases, traditional recommendation systems require significant computational resources to compute similarities and predictions.

3.2 Lack of Personalization for New Trends:

These systems heavily depend on historical data and may not quickly adapt to current user interests or trends.

Popularity Bias Frequently recommended items are usually the most popular ones, making it difficult for lesser-known or niche items to get visibility, even if they match a user's unique taste.

Limited to Explicit Feedback :Systems that rely mostly on explicit ratings may not function well when users do not actively rate or review items.

IV.PROPOSED SYSTEM

An embedding vector will be produced for a userID and one embedding vector for a movieID from the embedding space of 943 and 1682respectively. Then, the vectors are concatenated into one and then passed to the dropout layer. The dropout layer is used to avoid the over fitting of a model. In each training epoch,dropout randomly sets outgoing edges of the layer to 0 with some predefined probability. Next, several fully- connected hidden layers are added with a dropout probability and reLUactivation function. Each hidden layer can have a different value of output features and dropout probability. The input features are decided based on the output features of the previous layer. Finally, the predicted rating should be sentasan output for the input user and model IDs. For this, an output layer with a sigmoid activation function is employed and laterrescale in the range of 1 to 5. The weights of the neurons in each layer are updated in each training epoch with a backpropagation algorithm. The structure of our proposed network used as our model for predicting ratings

4.1 ADVANTAGES

Captures Complex User-Item Relationships: Using embedding layers allows the model to learn latent features of users and movies, capturing subtle and complex patterns in user preferences.

Improved Accuracy: The model uses deep neural networks with fully connected layers, enabling it to provide more accurate rating predictions compared to traditional methods.

Reduces Overfitting: The inclusion of dropout layers during training helps prevent overfitting by randomly deactivating neurons, making the model more generalizable to new data.

Scalable and Flexible :Neural network- based models can scale well with large datasets and can be modified easily to include more features (like genre, time, user demographics).

4.2 System Architecture

Fig4.2 **System Architecture**

V. MODULE DESCRIPTION

This movie recommendation system is divided into several interactive modules that work together to provide users with personalized movie recommendations. The major modules include **Admin Module**, **User Module**, and **Recommendation & Visualization Module**. Below is a description of each:

1. Admin Module

Upload Movie Details: The admin is responsible for managing the movie database. This includes uploading information such as:

- Movie title
- Language
- Genre
- Release year
- Poster or trailer link

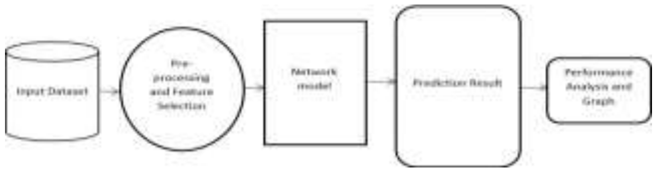
This module ensures that only authorized personnel can add or update movie data into the system.

2. User Module

User Registration/Login: Users must register or log in to access the system and interact with the movie data.

Movie Search Functionality:

Users can search for movies using keywords such **as** movie name **or** language**.**



This search helps users quickly find movies of interest from a large collection.

Give Ratings to Movies:

After watching or exploring a movie, the user can **rate the movie on a scale of 1 to 5**. These ratings are stored in the database and used to train the recommendation model.

View Your Rated Movies List:

Users can view a list of all the movies they have rated.

This helps users keep track of their interaction history with the system.

3. Recommendation & Visualization Module

Overall Rating Details: This module shows aggregated rating data for each movie.

Users can see how other viewers have rated a particular movie (average rating, total number of ratings, etc.).

Graphical Analysis:The system displays visual representations (graphs or charts) to show:

How much a movie is liked overall Comparison of user ratings for different movies Trends in user preferences This visual feedback helps users and admins understand movie popularity and user behavior.

Personalized Recommendations (if implemented):Based on the user's rating history and the deep learning model, the system can recommend movies that the user is likely to enjoy.

5.1 Summary of Functional Flow

i. Admin uploads movies.
ii. User logs in, searches movies, and gives ratings.
iii. Rated movies are saved and displayed in a user dashboard.
iv. System calculates and displays overall movie ratings.
v. Graphs provide visual feedback on movie popularity and user interaction.

VI.RESULT

The proposed movie recommendation model was evaluated using standard metrics: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). These metrics assess the accuracy of the predicted ratings against the actual user ratings.

6.1 Evaluation Metrics:

Root Mean Squared Error (RMSE): Measures the square root of the average squared differences between predicted and actual ratings.

Mean Absolute Error (MAE): Calculates the average of the absolute differences between predicted and actual ratings.

Performance Comparison:

The deep learning-based model demonstrated superior performance when compared with traditional machine learning algorithms like k-Nearest Neighbors (k- NN), Decision Trees, and basic Matrix Factorization techniques. The use of embedding layers significantly reduced the dimensionality and enhanced the model’s capability to generalize user preferences. The dropout technique effectively minimized overfitting, improving the model's performance on unseen data.

VII.CONCLUSION

In this work, a deep learning-based approach to movie recommendation has been proposed and implemented. By leveraging embedding layers for users and movies and constructing a neural network with dropout and ReLU activation functions, the system effectively learns non-linear user-item interactions. The results show that the deep learning model outperforms traditional recommendation techniques in terms of accuracy, as measured by RMSE and MAE. This validates the potential of deep learning in building more personalized and precise recommendation systems.

In conclusion, the proposed system not only enhances the accuracy of movie recommendations but also demonstrates scalability and adaptability to large datasets, making it a valuable tool for modern online platforms. Future improvements may include integrating additional contextual data (e.g., time, genre, or user demographics) and exploring advanced neural architectures such as recurrent or attention-based models.

VIII.REFERENCES

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