A Project Report

On

Movie Recommendation System using Collaborative Filtering and Deep Learning Techniques

Submitted by

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Chapter 1

Introduction

In the contemporary digital era, our daily activities often involve interacting with platforms like Amazon, Netflix, and Spotify, where we effortlessly view, purchase, and indulge in various forms of entertainment. Personalized recommendation systems are pivotal components of modern digital platforms, employing intricate algorithms to decipher user preferences and make tailored suggestions. Much like seeking advice from friends when choosing a movie, these systems utilize data filtering tools to recommend the most relevant items to each user [1].

In the ever-expanding realm of digital entertainment, the evolution of movie recommendation systems has become a pivotal facet in enhancing user experiences. This introduction delves into the fascinating realm of personalized movie recommendations, specifically focusing on collaborative filtering. As avid consumers of cinematic content, we often find ourselves navigating through vast libraries, seeking that perfect movie tailored to our unique tastes [2, 3]. The traditional approach of seeking recommendations from friends is paralleled in the digital landscape through collaborative filtering, a technique that harnesses user interactions and similarities to predict preferences.

Furthermore, this exploration ventures into the sophisticated domain of deep learning, an advanced neural network-based approach that has revolutionized recommendation systems which excel in extracting intricate patterns and representations from massive datasets, providing unparalleled accuracy in predicting user preferences. The synergy between collaborative filtering and deep learning unveils a new era in the art of suggestion, where algorithms not only understand user behavior but are also able to exploit the complex relationships within user interactions [4].

1.1 Motivation

This project is motivated by the increasing significance of personalized digital experiences in the realm of entertainment. As the demand for tailored content rises, understanding the intricate workings of recommendation algorithms becomes crucial. Delving into collaborative filtering and deep learning techniques, the report aims to unravel the magic behind cinematic suggestions, offering insights into how these technologies enhance user satisfaction and engagement. By exploring the synergy between collaborative filtering and deep learning, we seek to inspire a deeper appreciation for the innovative solutions shaping the future of personalized movie recommendations in the ever-evolving digital entertainment landscape.

1.2 Objective

This report aims to comprehensively investigate and elucidate the dynamics of movie recommendation systems, with a specific focus on integrating collaborative filtering and deep learning techniques. Through an in-depth exploration of these methodologies, the report aims to:

1. Provide a clear understanding of the role of collaborative filtering in personalized movie recommendations, emphasizing its user-centric approach.
2. Examine the transformative impact of deep learning on movie recommendation systems, elucidating how neural networks extract intricate patterns and latent features to enhance prediction accuracy.
3. Explore the synergy between collaborative filtering and deep learning, showcasing how their combined strengths create a more nuanced and effective approach to personalized movie suggestions.
4. Highlight the significance of personalized movie recommendations in the context of user satisfaction, engagement, and the evolving landscape of digital entertainment.

1.3 Contribution

The contributions of this report are as follows:

1. Empowered Decision-Making: Understanding movie recommendation systems with Collaborative Filtering (CF) and Deep Learning (DL) empowers users to make informed choices, appreciating the technology behind personalized suggestions and enhancing their overall viewing experience.
2. Inspiration for Innovation: The report inspires industry professionals, sparking innovation in recommendation systems by highlighting the combined impact of CF and DL and encouraging further exploration for refining algorithms and creating more accurate, user-friendly recommendations.

1.4 Organization

The introduction of this report is provided in Chapter.1 mentioning the applications, challenges, problems and solutions in movie recommendation followed by the motivation and objective of the thesis. Chapter 2 discusses the background and literature survey of our research in detail. Chapter 3 highlights the methods of our project work and experiments. Finally, Chapter 4 concludes the report.

Chapter 2

Literature Review

In this chapter, we present a brief overview of the literature related to the recommendation of the movies which further explores different types of movie recommendation methods, their challenges, and potential improvement recommendations.

Collaborative Filtering (CF) is one of the foundational approaches that rely on user interactions, which comprises three types: Memory-based CF, Model-based CF, and the Hybrid method, a combination of both. Further, Memory-based CF can be divided into three approaches: User-based CF [2], which suggests movies based on similar user preferences, creating a communal thread in movie choices; item-based CF [3] recommends movies with attributes akin to those the user has enjoyed, connecting the dots between movie characteristics, and the combination of user and item-based approach [5].

Complementing CF, Content-Based Filtering (CBF) takes a different route, considering user-profiles and movie content attributes. It enriches recommendations by aligning the features of movies with individual preferences, creating a personalized tapestry of suggestions [6, 7].

Regarding the model-based approaches, Matrix Factorization (MF) is the traditional method, while researchers have also applied Deep architectures for movie recommendation. MF [8] introduces a mathematical elegance to the landscape. Composing user-item interaction matrices unveils latent factors, capturing the intricate relationships between users and movies. However, Deep learning approaches, exemplified by neural collaborative filtering (NCF) [9], delve into complex patterns within vast datasets which employ neural networks, transcending traditional approaches to offer highly accurate predictions. Recently, neural networks like MLP, Autoencoder, RNN, and GNN enhance predictions by capturing intricate features. Further, by combining memory and model-based approaches, Hybrid CF often incorporates hierarchical prediction algorithms.

However, the movie recommendation journey is not without its challenges. The Cold Start Problem looms for new users or movies with limited data. Data sparsity exacerbates the issue, hindering the effectiveness of collaborative methods. As datasets grow, scalability becomes a concern, especially for computationally intensive algorithms. Solutions emerge in the form of hybrid and ensemble approaches. By combining collaborative and content-based filtering, these methods navigate the intricacies of individual limitations, enhancing recommendation robustness. Contextual information integration, considering factors like time, location, or user mood, elevates precision by tailoring suggestions to real-time scenarios. Hybrid models, incorporating demographic information, tackle the Cold Start Problem by making informed predictions with limited interaction history.

Chapter 3

Methods & Experiments

In this chapter, we discuss the dataset and its preprocessing, various CF methods, and the recommendation systems' Machine learning and deep learning approaches.

3.1 Dataset specification

We used the MovieLens 100K dataset [10] to evaluate the various models discussed in this report. The dataset was collected by the University of Minnesota's GroupLens Research Project. The dataset and its specifications are discussed in Table 3.1

No. of Users	610
No. of Movies	9724
No. of Valid Ratings	100836
(Minimum, Maximum) rating	(0.5, 5.0)
(Mean, Std) rating	(3.5, 1.04)
Train-Test Split	90-10

Std: Standard Deviation

Table 3.1: Dataset specifications

The collected dataset encompasses a significant volume of information, including details on users, movies, and their interactions. We employed histograms and scatter plots to visualize the dataset to uncover trends and outliers, which clearly give ideas of the dataset's characteristics.

The visual investigation established the groundwork for well-informed decision-making during subsequent phases of model development, guaranteeing a thorough comprehension of the intricacies of the dataset. Figure 3.1 clearly shows that most movies have less than 50 ratings. The number of movies having more than 100 ratings is very low. Further, Figure 3.2 shows that most of the provided ratings are in between 2-4.

3.2 Collaborative Filtering

Collaborative Filtering is a recommendation system technique that predicts a user's preferences based on the preferences of other users. It identifies patterns and similarities in user behaviors, recommending items liked by users with similar tastes. Two main types

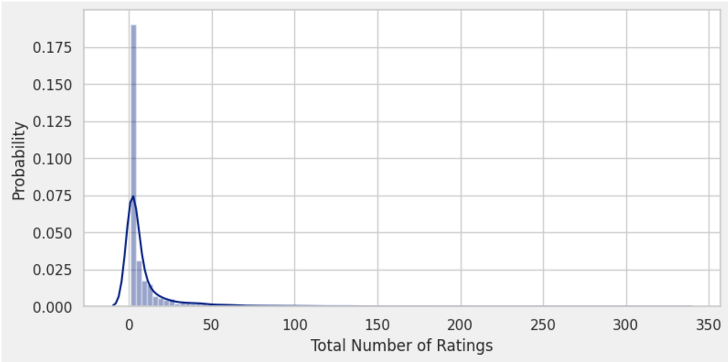

Figure 3.1: Probablity Mass Function (PMF) with respect to the total rating

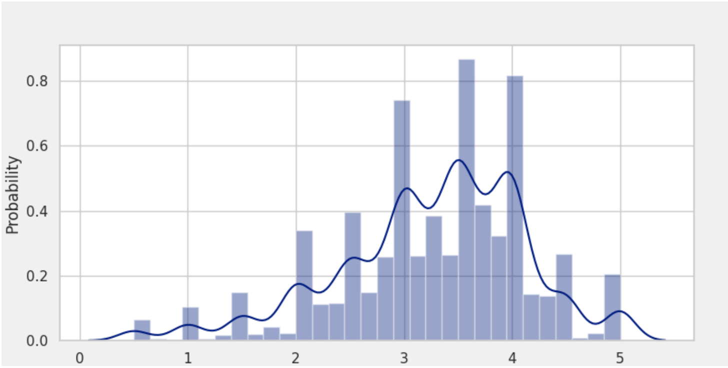

Figure 3.2: PMF with respect to the rating

are **user-based**, which suggests items liked by similar users, and **item-based**, which recommends items similar to those the user has already liked. Collaborative Filtering is widely used for personalized content recommendations in various domains, including movies, music, and products. To show the effectiveness of various methods, we employed several techniques as follows:

3.2.1 Memory Based CF

In our experiment, we employed both user-based and item-based memory-based collaborative filtering approaches to show the effectiveness of each type of memory-based method. Each method computes PCC similarity 1 among users and movies based on available ratings. It then computes. It then predicts a user's rating for a movie based on other users or movies. PCC is defined as follows:

Definition 1 (Pearson correlation coefficient[1] (PCC))**.** *Given two m dimensional vectors* $V_i, V_j \in \mathbb{R}_+^m$, *$PCC(V_i, V_j)$ is defined as follows:*

$$PCC(V_i,V_j) = \frac{\sum_{k=1}^{m} (V_i(k) - \bar{V}_i)(V_j(k) - \bar{V}_j)}{\sqrt{\sum_{k=1}^{m} (V_i(k) - \bar{V}_i)^2}\sqrt{\sum_{k=1}^{m} (V_j(k) - \bar{V}_j)^2}} \tag{3.1}$$

where $\bar{V}_i$ and $\bar{V}_j$ are the mean of V_i and V_j, respectively. ■

[1] https://en.wikipedia.org/wiki/Pearson_correlation_coefficient

It may be noted that PCC measures the linear correlation between two vectors. It is the ratio between the covariance of V_i and V_j and the product of their standard deviations. PCC is a normalized covariance measure; hence, the value ranges from -1 to 1. Here also, V_i and V_j are either the rating vectors of two users or two movies [1].

We discuss the user-based and item-based CF methods as follows: User-Based Collaborative Filtering / Item-based CF is a type of memory-based collaborative filtering used in recommendation systems. It relies on the assumption that users who have agreed in the past tend to agree again in the future. In other words, it recommends items based on the preferences of users who are similar to the target user. The following is the procedure for predicting the rating of movies using either the user-based or item-based CF approaches.

1. *Similarity Calculation using PCC:* Compute the similarity between the target user/movies and other users/movies in the system.

2. *Neighborhood Selection:* Identify a subset of users/movies (neighborhood) who are most similar to the target user/movies. This subset is used for making recommendations.

3. *Rating Prediction:* Predict the target movie rating for an item by aggregating the ratings of the selected neighborhood. Weighted averages or other aggregation methods are commonly used.

The advantage of a memory-based technique is that it is intuitive and easy to understand. It captures user/movie preferences without requiring any extensive contextual information about users and movies. The main challenge of this approach is that computational complexity increases with the increase of number of users/movies. Also, this approach fails when a a new user/movie is added to the system, commonly called a cold-start problem. We now discuss the model-based CF approaches.

3.2.2 Model Based CF

Model-based CF techniques are an alternative approach to memory-based collaborative filtering in recommendation systems. Unlike memory-based approaches that directly compute similarities between users or items, model-based methods build a predictive model based on the entire dataset. It utilizes machine learning algorithms to learn a model from the user-item interactions in the dataset. We employed three different model-based approaches in our methods, which comprise the following:

- **K-Nearest Neighbors (KNN)** is a memory-based collaborative filtering method that can also be used in a model-based context [11]. It involves finding a set of K similar users or items to the target user or item. In model-based CF, KNN can be used for item-based collaborative filtering by identifying a neighborhood of similar items for recommendation. To employ KNN, we compute mean squared distance similarity with a 5-fold validation technique.

- **Singular Value Decomposition (SVD)** is a model-based collaborative filtering technique that decomposes the user-item interaction matrix into three matrices: user matrix, item matrix, and a diagonal matrix of singular values [12]. SVD is

Table 3.2: Performance analysis in terms of RMSE

Model Name	RMSE
K-Nearest Neighbours (KNN) [11]	0.9396
Non-Negative Matrix Factorization (NMF) [4]	0.9224
Singular Value Decomposition (SVD) [12]	0.8726
Neural Collaborative Filtering (NCF) [9]	**0.1987**

widely used in recommendation systems to capture latent factors and make predictions based on these factors. It is effective in handling sparsity and providing accurate recommendations. We use dimensionality reduction methods to improve the robustness and accuracy of Memory-Based CF. Basically, we compress the user-item matrix into a low-dimension matrix. We use techniques like SVD, which is a low-rank factorization method, PCA, which is used for dimensionality reduction, etc.

- **Non-Negative Matrix Factorization (NMF)** is another model-based approach that factorizes the user-item matrix into two low-rank non-negative matrices representing users and items, aiming to discover interpretable patterns [4]. The advantage of the NMF is that it can handle the sparsity and cold start problems. Further, NMF is commonly used in CF to provide recommendations based on the learned factorization.

3.2.3 Neural Collaborative Filtering

Neural Collaborative Filtering (NCF) is a technique employed in recommendation systems to model user-item interactions through neural networks. Using deep neural networks, the goal is to learn the complex and non-linear features present among the user and movies [9]. NCF leverage the embedding layers to represent users and items as dense vectors. These embeddings capture latent factors that influence user preferences and movie characteristics. To implement the NCF methods, we exploit neural network architecture consisting of input layers for user and movie indices, embedding layers for each user and movie, one dense layer and finally, a merging layer to combine the user and movie embedding that learns dot products to generate the rating among them. This structure allows the model to learn the interactions between users and items. We subsequently apply layers as follows: Our NCF model consists of a 50-size embedding of each user and movie, a features concatenation layer and dense layers of 256 neurons followed by dropout layers for providing some regularization, which finally forced to one neuron to give the rating values applying the sigmoid activation function. Once trained, the model can predict user ratings for items that were not seen during training, enabling personalized recommendations. This way, NCF leverages the expressive power of neural networks to learn intricate patterns in user-item interactions for accurate movie recommendations.

The comparative analysis of each method is shown in Table 3.2, which clearly shows that deep learning approaches outperform the conventional memory-based and model-based CF approaches.

Chapter 4

Conclusion

In conclusion, we developed a movie recommendation system based on a few traditional approaches along with recent approaches. We began with an exploration of the dataset, meticulously analyzing user-item interactions and preprocessing the data to ensure its integrity. We first employed basic collaborative filtering approaches based on user-based methods and item-based methods. Further, we leverage a few machine learning approaches such as K-Nearest Neighbors, Singular Value Decomposition (SVD), and Non-Negative Matrix Factorization (NMF) as part of the model-based collaborative filtering. Finally, deep learning approaches to neural collaborative filtering was analyzed which performed best among all the method. We evaluated the performance of the employed models using Root Mean Squared Error (RMSE), a common metric for assessing recommendation system accuracy. This quantitative measure helped us gauge the performance of our models in predicting user ratings for unseen items.

In essence, our journey encompassed the extraction and exploration of the dataset, the implementation of two distinct model architectures, and the evaluation of their performance using advanced techniques in collaborative filtering and deep learning. This project has not only provided us with valuable insights into the intricacies of recommendation system development but has also showcased the versatility of matrix factorization in capturing complex user-item interactions.

As we move forward, the lessons learned from this project will undoubtedly contribute to our understanding of developing effective and scalable recommendation systems, and the techniques employed can serve as a foundation for future endeavours in the realm of personalized recommendation systems with user and items contextual information.

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