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Review of Movie Recommendation System

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***Abstract*— A movie recommendation plays a crucial role in our social life. A recommendation system provides a set of movies to the users based on the movie's popularity or depending on the users' interests. A recommendation system is also used to propose goods to buy or view. They employ an extensive collection of information to steer consumers to the things that will best match their needs. This paper discusses various movie recommendation algorithms used in recent research. We have summarized the movie recommendation algorithm's methodology, merits, and demerits. Moreover, we have discussed the future challenges in the movie recommendations system.**

Keywords— Movie recommendation, Machine learning, K-Nearest Neighborhood Algorithm, Deep learning.

I. INTRODUCTION

The increase of e-commerce has led the recommender system (RS) to change rapidly practically in every area. Recommender systems are data-filtering programmes that aim to forecast user and item ratings, primarily from big data, to propose their interests. These methods have been used in various applications, including movie and music, news recommendations, document and books recommendations. Many businesses have deployed these systems and have been benefitted extensively, such as Amazon's book recommendations, Apple Music's recommendations, and TaoBao's merchandise recommendations[1]. Users can utilize movie recommendation systems to help them categorize people who have similar interests. As a result, recommender systems are becoming an increasingly important aspect of e-commerce and websites applications[2].

These recommendation systems have become an essential part of many e-commerce applications. In one of two ways, recommender systems are used to collect information on a user's preferences for various commodities (e.g., movies, books, shopping, tourism, television, taxi): implicitly or explicitly. It is a systematic method of acquiring implicit user information to observe the user's activity, such as movies watched, products purchased, and software downloaded. On the other hand, direct information acquisition usually requires acquiring the user's previous ratings or interests. There are various techniques among them. Collaborative filtering (CF) is a technique used for filtering objects based on the feelings of other individuals. It gathers individual movie ratings before proposing films to the target user based on previous interactions with people with similar interests and tastes. Specific recommender systems are based on another perception called clustering. Clustering is an unsupervised data mining approach that divides a dataset into homogeneous groups based on similarity or dissimilarity metrics[2].Search engines are one of the most well-known filtering systems, which have gained widespread acceptance by making it easier for consumers to find items. There are recommender systems, which are gaining popularity due to their effectiveness in reducing the complexity of search space for consumers. The increased availability of similar things on the Internet makes finding reliable and relevant information by efficiently selecting the product exposed to it critically. Rather than creating a big epitome, recommenders help reduce preference models. There are a variety of recommenders available, including content-based, collaborative, hybrid, mobile4, and preference-based [3]. Besides, the always expanding blast of promptly accessible data about clients and things on the Internet makes it more basic than any time in recent memory to consolidate and join numerous perspectives or aspects of such data (for example, appraisals, social trust, literary and multi-media data) in the cycles normally completed by customary recommender models. "This may further develop proposal exactness and quality as well as might sometimes lighten probably the most much of the time tracked down deficiencies and weaknesses in recommender approaches [4].Some systems, for example, pay close attention to the need to restart the calculation if the user's interest changes. As a result, problems like cold start are known, which will occur when a new item or person appears, as their interests and belonging are unknown. Thus offering a new intelligent recommendation approach based on time-dependent interactions with Markov chains and DBSCAN genre grouping to address these issues. To put it another way, a recommendation system can reflect user preferences in an n-dimensional space based on clusters discovered, allowing users to track the progression of their interests and find the closest objects in a Euclidean distance space [5]."Recommender systems are more popular and increase the production costs for many service providers as the world's population increases today, and recommendations are required to recommend products or services. However, recommender systems minimize the transaction costs and improve the quality and decision-making process to the user". It is used in various related fields, including information retrieval and human-computer interaction (HCI). It collects a large amount of data on user preferences for various commodities such as books, online shopping products, music, movies, taxis, tourism, restaurants, etc. It saves data in a variety of formats, both positive and negative. It collects user feedback on movies they have seen, places they have been, and things they have bought. The movie recommendation system design presents a significant challenge when comparing demand from purchasing products and service providers (travel and restaurants). Other recommendation systems rely on service providers and product distributors to provide quick calculation and processing services[6].A recommendation system's primary goal is to predict how a specific user will rank an item. It helps the user choose the best option from a selection of alternatives. Many businesses, such as Netflix, YouTube, and Amazon, use recommendation systems to serve their customers better and increase profits. What we buy nowadays is based on recommendations. For example, if we wish to buy books, listen to music, or view movies, a recommendation system in the background makes recommendations based on the user's previous behaviours. Many platforms, such as Netflix, which recommends movies, Amazon, which recommends things, Spotify, which recommends music, LinkedIn, which recommends jobs, and any social networking site that recommends members, all rely on a recommendation system. Users may simply find out what they want based on their preferences using these recommendation engines. As a result, developing an effective recommender system is difficult because user preferences change over time. The phrase "recommendation system" refers to various issues used in many different industries. People use suggestions since they save time. Hence they are helpful in a range of sectors. It is used in various real-world scenarios, such as entertainment, e-commerce, services, and social networking. When watching movies, listening to music, or watching any TV show, recommendation algorithms are widely used in the entertainment sector. "When it comes to E-Commerce, Amazon is the largest shopping site on the planet. Some people use it to buy books, and others use it to buy a home or other things, while others still use it to buy clothes [7]. The remaining of the paper is organized as follows. Section II discuss related work, and we have summarized the merits and demerits of the different movie recommendations methods. Finally, we have concluded in section III.

II. Related work

Many research papers have illustrated the use of various machine learning deployed in movie recommendation systems; most of the research includes K-Nearest Neighbourhood (KNN) and the Deep Learning algorithms, which have been successfully employed in the movie recommendation system. This section discusses recent research work carried out in the Movie Recommendation System using a deep learning algorithm. Yadav, Ashima et al. combined the Bi-LSTM and Inception V4. LSTM layers, as well as a groundbreaking deep affect-based movie genre classification framework, in order to obtain discriminative and complete top features. The EmoGDB dataset is used, which contains 100 Bollywood movie trailers from six different genres. The main benefit of this innovation is that the architecture can classify the information without watching the complete movie trailer. Experiments proved that the suggested framework outperforms all state-of-the-art and alternative methodologies, demonstrating better performance and efficacy. Face expressions can be used to distinguish between different emotions. Thus they start by eliminating video frames that feature faces. Second, the ILDNet architecture is used to learn spatial and temporal features. Finally, emotion-based multiple genre identification hypotheses were established based on feelings to classify movie trailers into numerous genres. Run several trials on the LMTD-9, MMTF-14K, and ML-25M datasets, which produce AU(PRC) values of 0.81, 0.94, and 0.89, respectively, to validate the suggested architecture's performance[8].

Walek et al.developed a hybrid recommender system for making appropriate movie recommendations. A recommender module is included in this system, a hybrid that combines all the three systems a content-based system, collaborative filtering system and a fuzzy expert system. The proposed method analyses the user's favourite and least favourite genres etc. The system uses collaborative filtering and content-based algorithms to build the recommender module. The recommender system is wholly implemented as a web application. The dataset used to develop the proposed recommender system contains 100,836 ratings from 610 people on 9724 movies. This property gives movies the most significant expected rating, propelling them higher on the list of suggested films [9]. Li, Anchen et al. used implicit relations (IRec) that takes advantage of implicit user-user and item-item relationships. IRec is divided into two sections: neighbour construction and a recommendation framework. The first step is to create an implicit neighbour set for each person and object. The implicit neighbours for persons and things are discovered by mapping each network to a latent continuous space. The model is developed and evaluated using four: movie, business, book, and restaurant. The result shows that the model outperforms [10].

Chen et al. present the hybrid approach to suggest movies that customers will appreciate. This method varies from previous research in that it not only uses the user's positive preference outline to keep favoured movies and eliminate disliked movies, but it also uses the user's negative preference outline. The presented model improves movie recommendations' accuracy compared to the old content-based recommendation method. The collaborative filtering (CF) algorithm was used in this study to calculate the user's projected score for all objects, allowing the user's preferences to be divided into two groups: positive and negative. Using the dataset as an example explains how to generate an adverse user profile. Due to the popularity of scoring data, negative profiles can be transferred to other similar recommendation apps. If no scoring information is obtainable, a new model for extracting the user's adverse profile from the data should be devised, excluding wrong concepts further and improving overall performances [11]. The main research question is how to build and use a knowledge network representing human emotions for movie selection. Breitfuss et al. applied critical technologies such as knowledge graphs, natural language processing, and deep learning in the movie recommendations system. Emotional reasoning was exhibited using a chatbot, and a knowledge network was created based on the users' emotions. The constructed knowledge graphs were made public, and a study on performance and prevailing emotions were carried out. The representation of emotions is also demonstrated to evolve, making it worthwhile to regularly construct new versions of the knowledge network [12].

Vilakone et al. used k- cliques and cosine similarity algorithms. There are two types of data in this dataset: experimental and test data. The number of movies to be rated by the new user among the movies recommended by the system was projected when constructing the proposed movie recommendation system utilizing better k-cliques. To compare the performance of the suggested recommendation system, this study uses the most generally used assessment metric. The mean absolute percentage error is a formula-based methodology to predict the accuracy of a forecasting method in statistics (MAPE). The maximum clique social network analysis technique suggested in this paper is the first time employed in a movie recommendation system, and the findings are pretty compelling. The k-clique method, which is particularly effective in social networks, was used in this experiment to improve accuracy. The findings proved the method's effectiveness. The maximum clique strategy proved to be more effective. As a result of this study, an improved k-cliques approach was developed for selecting the most efficient solution [13].

Collaborative filtering and the K mean approach is proposed by Furtado et al. A list of movies based on the user's earlier ratings will emerge when he hits the "Generate Recommendation" button. He is supposed to utilize the "search" box to locate a random film that piques his interest and rate at least six films if he is a new user who has not yet rated any films. After that, the "Generate Recommendation" button will become available. While this collaborative system analyses the relationship between various clients and, based on their ratings, recommends movies to others who have similar tastes, users can expand their horizons. It is a web-based programme that allows users to assess movies and then recommends suitable films based on the ratings of others. [14]. Ananya et al. examine different strategies like Hybrid Filtering, Hadoop, and the K-implies Algorithm. The information for this review came from the Yahoo Research Web scope data set. Yippee! Motion pictures User Ratings and Yahoo! Clear Content Information are the two records given. They look at the Item-based comparability coefficient by planning the Movie ID of Movie 1 and 2 to their titles. Uses the Average Absolute Difference Recommender Evaluator to assess a client-based recommender framework model. The preparation information is partitioned into test and train tests. The rating expectations on test information contrast with the genuine appraisals indicated in the preparation information. Have executed a film proposal framework utilizing communitarian separating. It is executed utilizing Apache Mahout and takes the appraisals given to motion pictures to give film ideas. Our framework considers the client appraisals to suggest motion movies [15].

The main phases in differential privacy protection system, prefix tree privacy budget allocation technique, and prefix tree privacy budget allocation algorithm were employed by Li, Min et al. The dataset utilized are the MovieLens 1M, which has 100 million ratings from 6,000 people on about 4,000 films. This work primarily discussed how to build a differential privacy protection approach in a movie recommendation system to secure users' privacy while guaranteeing that the recommendation system's performance is not jeopardized. Experiments show that this strategy can balance safeguarding users' privacy and keeping the recommendation system performing well[16]. Ashrita et al. utilized different recommender frameworks, for example, multi-standards recommender frameworks, hazard mindful recommender frameworks, versatile recommender frameworks, and half and half recommender frameworks. The Movie Lens tiny dataset will be analyzed, emphasizing two records: movies.csv and ratings.csv. Presented Movie REC, a film suggestion recommender framework. It permits a client to browse an assortment of traits and afterwards prescribes a film rundown to him dependent on the aggregate load of the different properties and the K-implies calculation. Because of the idea of the framework, assessing execution is troublesome because there is no right or mistaken proposal; it is only a question of assessment, which got a positive response from a bit of gathering of clients in the wake of doing casual assessments. We needed to have a more extensive information assortment with the goal that our calculation could create more significant discoveries. Additionally prefer to try different things with elective AI and grouping calculations and look at the results. They at last need to foster an online UI with a client data set and a learning model that is modified for each utilization [17].

Wang et al. reported that several collaborative filtering and content-based hybrid recommender systems were used in this investigation. User data, movie data, and review data are the three types of Douban movie data. The sentiment analysis results applied to movie reviews are used to evaluate a preliminary suggestion list. Sentiment analysis might be able to help you narrow down your film choices. Consequently, the model performs better when combining collaborative filtering and a content-based technique with sentiment analysis. Our technique outperforms straightforward recommendations in terms of actual positive rate, indicating that the algorithm is better at suggesting relevant films. The findings show that the proposed method is precise and efficient [18]. Keshava et al. presented the XGBoost, Suprise KNNBaseline Predictor, Matrix Factorization SVD, Matrix Factorization SVDpp, User-Item Sparse Matrix, User-User Similarity Matrices, User-User Similarity Matrices, User-User Similarity Matrices, User-Item Sparse Matrix, User-User Similarity Matrices, Matrix Factorization SVD

Dataset According to the graph, the essential attributes are user average and movie average. In contrast, baseline user is the least important feature. And the baseline model's error rates. All models' RMSE and MAPE are trained and tested. The comparison of all models with error levels is shown in the graph above. SVDpp is the best model, with a Test RMSE of 1.0675. They do not have to be concerned about our RMSE because they have not trained it on all data[19].

In this paper, Kapoor et al. propose using SVM, KNN, Text Mining, Android Application Model, Movie Ranking Approach, and Flask Server. The Movie Database (TMDB) is a well-known database that houses a wealth of information on films, television shows, and actors. The work's results may be separated into two categories: first, the results of the machine learning model trained to analyse sentiment in reviews, and second, the performance of the movie ranking algorithm in rating and recommending movies. We have a dynamic dataset that develops over time (since people will not stop providing reviews, right?). With more and more data-focused on expanding our research, the

SVM model achieves an accuracy of close to 85% in categorizing a review as positive or negative. After the app's successful testing, they hope to develop the rating system into a movie recommender system. Users will receive recommendations based on their viewing history and preferences, following the successful testing of the application [20]. Chauhan et al.propose KNN collaborative filtering algorithm. The system's operation will recommend a user login system that must gather all of the user's behavioural attributes and store them in the user's database in the user's login module model. After logging into the system, the system makes recommendations to the movie's users depending on their recommendations. This paper proposes and explains the basic concepts of movie recommender systems based on user sentiment [21]. Agrawal et al. The paper involves various methods such as the Hybrid method, Simple Support Vector Machine (SVM) Algorithm, Adjusted K-Means Algorithm, Genetic Algorithm, and Cosine Similarity Measure. Movie Lens 1M, Movie Lens Latest Small, and Movie Lens 10M datasets are all available. The results show that applying the proposed methodology to three different Movie lens datasets increases the accuracy. The suggested approach takes less time to compute. However, it requires more memory than the existing pure content-based or pure collaborative model. Comparative results reveal that the suggested approach outperforms pure alternatives in terms of accuracy, quality, and scalability of the movie recommendation system. Furthermore, the proposed solution takes less time to compute than the other two pure alternatives [21].

TABLE I. COMPARISON OF MOVIE RECOMMENDATION DEEP LEARNING ALGORITHM

References	Method	Merits	Demerits
[8] Ashima Yadav, Dinesh Kumar Vishwakarma .	Deep neural networks for genre classification	The proposed deep neural network gives better precision, recall, F1 score, precision-recall, curves, and AOC than SVM, KNN and CNN.	Emotion categories of trailers are complicated when the input is only facial expressions.
[9] Bogdan Walek , Vladimir Fojtik .	Expert system for recommending relevant movies	The proposed approach suggests appropriate films. The final list of suggested films is computed by a fuzzy expert model that assesses the relevance of the films. The method works with the user's favourite and least-liked genres.	This paper does not cover work with favourite and unpopular movie genres. If a user marks "comedy" as an unpopular genre, the algorithm will suggest something else.
[10] Anchen Li , Bo Yang , Huan Huo , Farookh Khadeer Hussain.	Leveraging implicit relations for recommender systems	The proposed approach includes an innovative technique for implicit mining user-user and item-item associations and a natural manner to exploit these relationships for a recommendation.	To improve recommendations, the work does not include incorporating side data into implicit relations, such as information graphs and social webs.
[11] Yen-Liang Chen , Yi-Hsin Yeh , Man-Rong Ma	Movie recommendation method based on users' positive and negative profiles	The proposed CF algorithm is used to calculate the user's projected score for all objects, allowing the user's preferences to be divided into two groups: positive and negative.	The demerits include identifying the user's unfavourable preferences is difficult. They used the collaborative filtering algorithm only to generate the user's expected score for all items in this study.
[12] Arno Breitfuss, Karen Errou, Anelia Kurteva and Anna Fensel.	Representing Emotions with Knowledge Graphs for Movie Recommendations .	In movies, the proposed knowledge network represents human emotions—machine learning techniques applied to take emotions from pre-existing movie evaluations. A chatbot prototype has been created to demonstrate how the knowledge graph may be used.	As the Markov Chains are context-insensitive, more investigation is needed in NLP. The classification jobs could have been better, and the Naive Bayes approach could have been inefficient.
[13]Phonexay Vilakone, Doo-Soon Park, Khamphaphone Xinchang & Fei Hao (2018).	Efficient movie recommendation algorithm based on improved k-clique	This work provides an effective movie recommendation algorithm based on modified k-clique algorithms with the highest recommendation accuracy.	The effectiveness of the method depends on the K-clique algorithm parameters.
[14]Furtado , A, Singh.	Movie Recommendation System Using Machine Learning	The proposed model includes combining both content-based and collaborative approaches. This model gives better accuracy than the traditional movie recommendation system	The demerit is that the collaborative approach deals with the cold start problem.
[16] Min Li , Yingming Zeng , Yue Guo , and Yun Guo.	Movie recommendation system Based on differential privacy protection	This study investigates the encryption interference caused by a differential privacy defence strategy on user data's local policies. The proposed method includes a dynamic privacy budget allocation.	However, several unresolved topics should be investigated in both the disciplines of differential privacy and recommendation algorithms.

Future challenges in Movie recommendation system:

1. Cold Start

This issue emerges when new clients or new things are added to the framework. Another thing cannot be prescribed to clients when it is acquainted with the proposed framework without appraising or surveys. Thus, it is challenging to foresee clients' decisions or interests, prompting less exact suggestions.

Another client or thing added based issue is hard to deal with. For instance, a recently delivered film cannot be prescribed to the client until it gets a few appraisals. It is challenging to acquire a comparable client without knowing past interests or inclinations.

2. Synonymy

Synonymy emerges when a solitary thing is addressed with two distinct names or postings of things with comparable implications. In such condition, the suggested framework cannot perceive whether the terms shows different things or a similar thing. For instance, suggestion frameworks anticipate 'activity film' or activity film' something similar.

3. Privacy

Precise necessities to take care of his data (have involvement in hyper-personalization) to the proposed framework for more useful administrations however it causes the issues of information protection and security, numerous clients feel faltering to take care of their information into suggestion frameworks that experience the ill effects of information protection issues. The proposed framework will undoubtedly have clients' data and use it to the fullest to give customized suggestion administrations. To manage this issue, the proposal frameworks should guarantee trust among their clients.

4. Scalability

One most significant issues is the adaptability of calculations having open world datasets under the proposed framework. Client thing associations produce enormous changing information as evaluations and audits. Like this, versatility is a significant worry for these datasets. Suggestion frameworks decipher results on enormous datasets wastefully; some high level massive scaled strategies are needed for this issue.

5. Latency

We notice numerous items are added as often as possible to the data set of suggestion frameworks, just previously existing items are prescribed to clients as recently added items are not evaluated at this point. So an issue of Latency emerges. The synergistic separating strategy and class-based methodology in the mix with client thing communication can manage this issue. Figure 1 shows the Future challenges in the movie recommendation system.

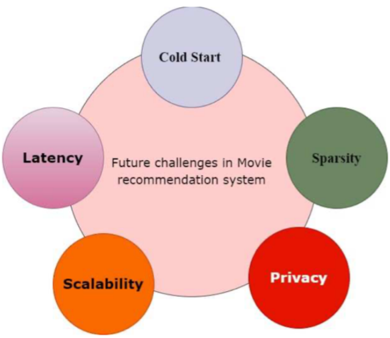

Figure 1: Future challenges in movie recommendation system

III. Conclusion

Recommendation System has been extensively used in all platforms such as movies, books, music, etc., one of the biggest boons to the people and many industries facing many problems and challenges to solve the issue. However, the emerging field of machine learning has become an effective problem solver tool with many issues, same as that of movie recommendation systems. In this paper, the literature review is made by collecting the various research papers which have proved the use of machine learning algorithms in the movie recommendation system where different datasets with many attributes were used to recommend movies and their accuracy was compared with other algorithms of higher accuracy. Hence, machine learning has solved many unresolved challenges, and the recommendation system is used everywhere, which is never-ending. The use of the right tool at the right time helps recommend the movies to the users. However, in this internet era recommendation system is a compulsory process.

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