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Major Challenges of Recommender System and Related Solutions

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ABSTRACT- Recommender system is a very young area of machine learning & Deep Learning research. The basic goal of the recommender system is to create a relationship between items and consumers. The relationship provides recommendations based on user interest. content-based, collaborative, demographic, hybrid filtering, knowledge-based, utility-based, classification model are well-known recommender models. The model uses an item's specifications in content-based filtering to suggest other objects with similar features. Collaborative filtering takes into the user's previous activity which means the user has previously viewed or purchased, as well as ratings Provided by the user to those items and similar conclusions reached by other users' item lists. View user profile data such as age category, gender, education, and living area to detect commonalities with other profiles.[31] All three filtering techniques are used in hybrid filtering. In the process of recommendations, various challenges are faced by the system. So, this paper lists various solutions by researchers in recent days.

KEYWORDS- Recommender system, content-based filtering, collaborative filtering, Deep Learning.

I. INTRODUCTION

Recommender System: A recommender system is a computer program that makes recommendations to a user based on a variety of parameters. These methods anticipate which items are most likely to be purchased and which people are most probably interested in. Companies such as Youtube, Walmart, and others[32] utilize recommender platforms to assist their consumers locate the right product or film.

The recommendation systems use filters to deal with vast data [33]. The most essential report is based on user information and other criteria that consider the person's preferences and interests. It recommends based on the compatibility of the user and the object and the similarities between users and goods.

II. TYPES OF RECOMMENDER SYSTEM

A. *Collaborative Filtering*

Collaborative filtering is the process of predicting a user's interest based on a large
number of users' choices and data. This is performed by using tactics that require collaboration across various agents, data sources, and other elements to look for information or identify patterns. Collaborative filtering is based on the assumption that if customers A and D have similar tastes in one item, they are likely to have similar tastes in other products as well [32]. Memory-based and Model-based techniques are the two most common forms of collaborative filtering systems.

a)Memory-based approaches

This is also known as collaborative filtering in the neighborhood. Ratings of user-item pairs are simply predicted based on their proximity [33]. Collaborative filtering is further classified into 2 types: user-based collaborative filtering and item-based collaborative filtering. User-based simply means that strong and similar recommendations will come among like people. Item-based collaborative filtering suggests things based on perceived relevance, as determined by customer reviews.

- **User-Based:** The consumer methodology is used to discover users that have seen comparable material and to recommend new items' likes and dislikes [34]. Fig 1 shows a user-based model example.
  Similar users.

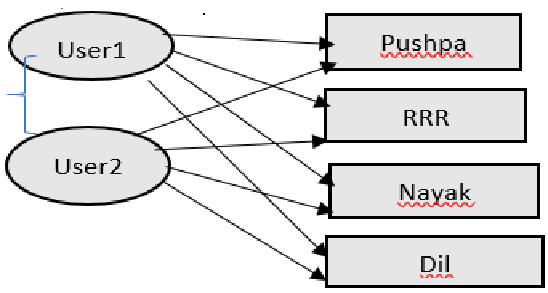

Figure 1: User-based model example

One disadvantage is there are typically far more people than things, resulting in a much more vast user identity matrix, which causes efficiency and storage concerns on huge datasets, forcing the adoption of parallelization techniques or other ways.

- **Item-based**: Instead of beginning with a certain film (or series of films), we search for relevant movies depending on some other customer selections [34]. Fig 2 shows an item-based example.

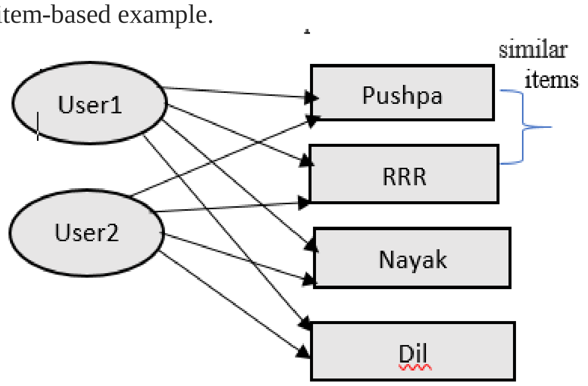

Figure 2: Item-based model example

b) Model-based approach: Machine learning and data mining techniques are used in those procedures. The idea is to create models which can forecast the future. We could, for instance, use existing user-item interactions to train a model that predicts a user's top-5 favourite items[34]. When compared to other methods like memory-based, these methods have the added benefit of being able to suggest a bigger amount of items to a significant number of individuals.

- Matrix Factorization: Matrix factorization is a technique for generating latent factors when two distinct types of firms are combined. In collaborative filtering, matrix factorization is utilized to establish the relationship between items and user entities. The following Table 1 illustrates user feedback for films.

Table1: User feedback for movies

	Movie 1	Movie2	Movie3	Movie4	Movie5
User1	5	1		4	3
User2		2			
User3	2		3	1	2
User4		3	2		
User5	3		1	5	

Because not every user assigns a score to all of the films. Because there are so much missing data, the matrix is sparse. As an outcome, any null values provided by users will be replaced with 0 so that filled values can be multiplied. If a movie is acted by their favorite entertainer and the category is drama, two people may give it a positive reputation [35].

- **Singular Value Decomposition:** The Singular Value Decomposition (SVD) is based on a linear method that is widely employed in computer vision as a features extraction tool. The SVD method is a matrix factorization approach for lowering the number of characteristics in a dataset by reducing the space dimension from N to K (where KN)[36].
- **Alternating Least Squares**: ALS recommendation system is an interchanging least-squares weighted-Lambda-Regularization (ALS-WR) matrix factorization technique [32].

***B. Content-Based Systems*:** These systems make suggestions based on a user's item and profile information. They believe that if a user has access expressed interest in something, they will do so again in the long term. Comparable commodities are frequently grouped based on their features. User profiles are created by analyzing previous conversations or straightforwardly asking people about their passions. Other systems use other systems that use user individual and interpersonal data that aren't regarded as purely content-based[32].

C. Hybrid Recommendation System: Pure recommendation system models have flaws and restrictions, which are addressed by hybrid filtering. The hybrid models bring together a variety of recommendation strategies under one roof in terms of improving advice precision while reducing the disadvantages of each. To alleviate the cold start problem, collaborative filtering is usually combined with other methods. However, as techniques can be integrated into a variety of ways [37], this is not a must.

a) **Weighted Hybrid Recommender:** In this system, the score of a recommended item is computed from the results of all of the available recommendation techniques present in the system [37].

b) **Switching Hybrid Recommender**: Switching Hybrid Recommender, switches between the recommendation techniques based on particular criteria. Suppose if we combine the content and collaborative based recommender systems then, the switching hybrid recommender can first deploy a content-based recommender system and if it doesn't work then it will deploy a collaborative based recommender system [37].

c) **Mixed Hybrid Recommender**: Where it's possible to make a large number of recommendations simultaneously, we should go for mixed recommender systems. Here recommendations from more than one technique are presented together so that the user can choose from a wide range of recommendations [37].

D. Popularity-Based Recommendation System:

It is a type of recommendation system which works on the principle of popularity and or anything which is in trend. These algorithms search for products or movies that are currently hot or popular among consumers and propose them right away. For example, if a product is often purchased by most people, then the system will get to know that that product is most popular so it will recommend it for every new user who just signed [37].

E. Classification Model

The categorization model is a type that analyses aspects of both items and users to predict whether or not a user will enjoy an item. When new customers arrive, our classifier will assign a binary value to that product, indicating whether or not the consumer might like it. This allows us to suggest a product to the consumer [37].Fig 3 shows the how classification done.

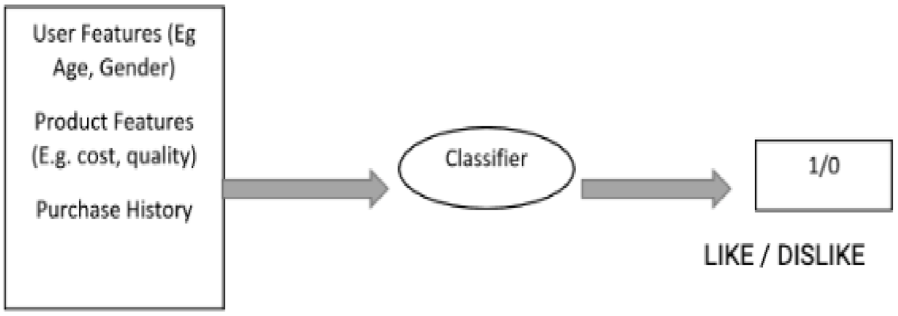

Figure 3: Classification model

In the above example, using user features like Age, gender, and product features like cost, quality, and product history, our classifier will give a binary value indicating if a user may like a product or not.

F. Demographic-based Recommender System

This system aims to categorize the users based on attributes and make recommendations based on demographic classes. Many industries have adopted this strategy because it is not overly complicated and straightforward to apply. In a Demographic-based recommender system, the algorithms first need proper market research in the specified region

accompanied by a short survey to gather data for categorization [37]. Demographic approaches, like collaborative ones, create "people-to-people" connections, but with different data. A demographic approach has the advantage of not requiring a history of user ratings, which is required by collaborative and content-based recommender systems.

G. Utility-based Recommender System

Utility means Measure of how useful the recommendation is for the user. This system makes suggestions based on a computation of the utility of each object for the user. The main issue with this type of system is figuring out how to make a utility for specific users. In a utility-based system, every industry will have a different technique for arriving at a user-specific utility function and applying it to the objects under consideration [37].

H. Knowledge-based Recommender System

The system makes recommendations using knowledge-based. It does not depend on the user rating and profiles, return products based on specific queries made by the user. For example, users searching houses online gave some inputs such as price, space, Rooms, etc, based on constraints it recommends houses [37].

III. CHALLENGES IN THE RECOMMENDATION SYSTEM

Cold start: Recommender systems are a type of information filtering technology that aims to present consumers with relevant information. A cold start occurs when the system is unable to build an association between persons and items for which it lacks sufficient data. Cold-start problems can be classified into two groups [31].

User cold-start problems: when there is almost no information available about the user

Product cold-start problems: When there is almost little understanding about a product, it is called a cold-start issue.

Privacy: In general, an individual must provide his personal information to the recommendation system to receive more useful services, however, this poses privacy and security concerns. Many people are hesitant to give their data to recommendation algorithms that have privacy concerns. Users' personal information will almost certainly be collected by the recommendation system, which will then be used to give customized recommendation services. Recommendation systems must ensure that their consumers trust them [31].

Gray Sheep: Gray sheep is a phenomenon that arises in collaborative filtering systems when a user's thoughts do not equate to any group and, as a result, they are unable to profit from recommendations. [31].

Scalability: The scalability of algorithms with real-world datasets under the recommendation system is one of the most significant issues. A large amount of changing data is generated by user-item interactions in the form of ratings and reviews, and hence scalability is a major worry for these datasets. [31].

Sparsity: It occurs frequently when the majority of users do not provide ratings or reviews for the items they buy, resulting in a sparse rating model that can cause data sparsity difficulties and limit the chances of finding a group of users with comparable ratings or interests. [31].

Shilling Attacks: This occurs when a malevolent person or rival gains access to a system and begins giving fake evaluations on items to boost their popularity.

Changing User Preferences: The problem is that today's users browse with a specific goal in mind. User preferences are changed every time most of the recommender system facing this issue.

Accuracy: It is hard to calculate in a recommender system but accuracy can be measured by using user*items Matrix. the relationship between a need and a possible recommendation [8].

Lack of data: The fact that recommender systems require a lot of data to provide excellent recommendations is perhaps the largest difficulty they face. It's no coincidence that organizations with a lot of consumer user data are more associated with having strong suggestions. [8].

IV. MAJOR SOLUTIONS FOR THE RECOMMENDATION SYSTEM CHALLENGES

The below table provides solutions to the issues faced by the earlier system. The solutions will help to overcome problems and introduce new techniques implemented in different papers. Table 2 shows related solutions to overcome the issues faced by recommender system.

Table 2: Solutions for different issues

SNO	Problem	Paper Name	Year of Publication	Abstract	Domain
1	Cold-Start	Solving Cold-Start Problem in Large-scale Recommendation Engines: A Deep Learning Approach	2017	To solve the cold-start problem, this work develops a product-to-product deep learning matcher based on document commonalities acquired from the state-of-the-art document embedding model doc2Vec and combines it with a CF-based recommender engine[25]	Deep Learning
2	Cold-Start	Resolving Cold Start Problem Using User Demographics and Machine Learning Techniques for Movie Recommender Systems	2018	The proposed method appears to be promising for producing recommendations for new users who have no previous experience with the system. Ensemble classification models are efficient and dependable in categorizing new users, as evidenced by their high classification accuracy and re-enforcing mechanism, after which prospective comparable users are selected out using the similarity factor metric [1].	Machine Learning
3	Cold-Start	A novel approach to solve the new user cold-start problem in recommender systems using collaborative filtering	2017	To predict item evaluations for a new user, this study used a three-phase approach: 1) Classification by users 2) Step Calculation of User Similarity 3) Forecasted User Rating Step [2]. Two matrices were used to predict accuracy MAE, RMSE.	Machine Learning
4	Cold-Start	Solution for cold start problem in Recommender system	2019	Several solutions were offered in this research. Active Learning, Semantic Attributes, Visual Features, Personality Traits, and Cross-domain Recommendation are the five groups of solutions [3].	ML&DL
5	Privacy	Privacy-preserving hybrid recommender system based on deep learning	2021	The accuracy of the Global differentially private method was measured using RMSE, MAE relative to baseline, global average, Item average, and User KNN Pearson in this study[4].	Deep learning
6	Privacy	A Practical Privacy-Preserving Recommender System	2016	This study proposes a privacy-preserving recommender system based on product similarity, which can protect a user's profile and rating history from prying eyes. It takes advantage of element cosine similarity [5].	Encryption

7	Privacy	Using a Hybrid-Based Deep Learning Method, an Accuracy-Assured Privacy-Preserving Recommender System	2020	This Paper proposes the Restrictive Boltzmann Machine Approach (RBM) and a hybrid deep learning approach, RBM with Convolution Neural Network (CNN) (CRBM). When compared to other current systems, these two proposed strategies improve the accuracy of the film recommender system [6].	Deep Learnin g
8	Privacy	Privacy-Preserving and Secure Recommender System Enhance with K-NN and Social Tagging	2017	This Paper proposes the Restrictive Boltzmann Machine Approach (RBM) and a hybrid deep learning approach, RBM with Convolution Neural Network (CNN) (CRBM). When compared to other current systems, these two proposed strategies improve the accuracy of the film recommender system [6].	Machine Learnin g
9	Privacy	Privacy-Preserving User-Based Recommender System	2017	A homomorphic encryption-based user-based CF technique canto detects user commonalities and then provide recommendations without revealing any personal information [7].	cryptogra phy
10	Gray Sheep	Fulfilling the Needs of Gray-Sheep Users in Recommender Systems, A Clustering Solution	2011	To discover these users, a clustering technique is given, and suggestions for these individuals are generated using SVM regression trained on the users' content profiles, while Cluster collaborative filtering is used to produce recommendations for other users. [8].	Machine Learning
11	Scalable	A Scalable, Accurate Hybrid Recommender System	2010	In this study, MAE is used to quantify variance between ratings by measuring cosine similarity, vector similarity between items using demographic and feature vectors, and cosine similarity between items using demographic and feature vectors [27].	Machine learning
12	Scalable	Scalable deep learning-based recommendation systems	2018	Each layer employs batch normalization-based, and the network is trained using backpropagation and the stochastic gradient descent method. The dropout method is primarily employed to reduce overfitting [9].	Deep learning
13	Scalable	Scalable Collaborative Filtering Approaches for Large Recommender Systems	2009	The Netflix Prize data set, which is currently the largest publicly available collection, is used to evaluate several scalable strategies presented in this study. It proposes several matrix factorization-based techniques (MF). Second, a method for MF neighbor rectification is provided [10].	Machine Learning
14	Sparsity	Transfer Learning for resolving sparsity problem in recommender system: Human Values Approach	2017	This research primarily uses the KNN model, with MAE and RMSE being used to assess mistakes, and Precision, Recall, and F1 are used to calculate model performance [11].	Machine Learning
15	Sparsity	Effects of Data Sparsity on Recommender Systems based on Collaborative Filtering	2018	This study examines three alternative methods, namely Non-negative Matrix Factorization, Singular Value Decomposition, and Stacked Autoencoders, under specific sparsity scenarios of the MovieLens 100k dataset to provide the effects of sparsity variations on recommender systems [28].	Deep Learning

16	Sparsity	Reducing Data Sparsity in Recommender Systems	2018	Preprocessing, similarity, and prediction are the three phases of the proposal's consequences. With a non-sparse matrix, using user-based and item-based prediction approaches may enhance prediction accuracy. MAE values should be reduced [12].	Machine learning
17	Sparsity	Handling data sparsity via item metadata embedding into deep collaborative recommender system	2021	The model is divided into two sections, the first of which uses a neural network to extract nonlinear properties from the data using embedding vectors. In the second stage of the model [13], these vectors are combined and used as input.	Deep learning
18	Shilling Attacks	Detecting Shilling Attacks Using Hybrid Deep Learning Models	2020	This paper provides a hybrid model of two distinct neural networks, convolutional and recurrent neural networks, to detect shilling assaults efficiently. The proposed deep learning model uses an updated network architecture to produce attributes from user-rated profiles [14].	Deep learning
19	Shilling Attacks	Robust Model-Based Reliability Approach to Tackle Shilling Attacks in Collaborative Filtering Recommender Systems	2020	This research provides a novel robust strategy for neutralizing shilling assaults based on matrix factorization[15].	Machine Learning
20	Shilling Attacks	Shilling attack detection in Collaborative Recommender Systems using a Meta-Learning strategy	2020	This paper uses the combiner technique to detect shilling assaults, which combines different classifiers. The diversity metric is used to select the most optimal group of classifiers. The k-Nearest Neighbour, Support Vector Machines, and Bayesian Networks were used as the initial basis classifiers in this paper. The Naive Bayes was used as a Meta Classifier [29].	Machine Learning
21	User preference	Learning Complex User Preferences for recommender Systems	2021	This paper uses a purpose-specific attention unit (PSAU) for the next-item suggestion task to pay attention to crucial items differently depending on the user's aims and preferences [16].	ML&DL
22	User preference	Recommendation System Based on Prediction of User Preference Changes	2016	The strategy consists of three steps. To obtain user features, first, use matrix factorization and purchasing time. Then, using a Kalman filter, estimate user preference vectors based on user features. Finally, we compile a list of recommendations [30].	Machine Learning
23	User preference	Adapting to User Preference Changes in Interactive Recommendation	2015	It uses a multi-armed bandit strategy to describe this online learning problem and presents methods for detecting changes in user preferences [17].	Machine Learning

24	User Preference	Modeling User Preferences in Recommender Systems	2014	This study proposes a categorization framework for the use of explicit and implicit user input in recommender systems, based on a set of distinct features such as Cognitive Effort, User Model, Scale of Measurement, and Domain Relevance [18].	Machine Learning
25	Unpredictable Items	Personalized Unexpected Recommender System for Improving User Satisfaction	2021	This study introduces the PURS (Personalized Unexpected Recommender System) model, which incorporates unexpectedness into the recommendation process. To improve unexpected suggestion performance, we also offer a novel unexpected activation function[19].	Deep learning
26	Inconsistency	Coherence and inconsistencies in rating behavior estimating the magic barrier of recommender systems	2018	It demonstrates a link between user coherence and the magic barrier, and we exploit this connection to distinguish between easy and difficult users [20]. It presents findings from studies in which the rating prediction error for more coherent users is lower than for less coherent users.	Machine Learning
27	Prediction Accuracy	Improving prediction accuracy of multi-criteria recommender systems using adaptive genetic algorithms	2017	The empirical findings show that the adaptive evolutionary algorithm-based multi-criteria recommendation technique gives significantly more accurate predictions than the traditional recommendation approach [21].	Neural Networks
28	Prediction Accuracy	Toward Improving the Prediction Accuracy of Product Recommendation System Using Extreme Gradient Boosting and Encoding Approaches	2020	By combining extreme gradient boosting machine learning architecture with the word2vec technique, the proposed system examines purchased products based on user click patterns. The accuracy of forecasting relevant products that are likely to be purchased by clients is improved by using an algorithm [22].	Machine Learning
29	Diversity	Diversity in Recommendation System: A Cluster-Based Approach	2021	With the Movie-Lens dataset, the suggested solution uses the K-means clustering algorithm to construct a customized movie recommendation system[23].	Machine Learning
30	Diversity	An Item-Diversity-Based Collaborative Filtering Algorithm to Improve the Accuracy of Recommender System	2018	This research presents an enhanced item-diversity-based recommendation approach that incorporates bias and unconscious feedback. Users like multiple options, according to the study and matrix factorization technique [24].	Machine Learning

V. CONCLUSION & FUTURE WORK

Today, recommender systems are a hot topic in academia& Industry. Increasing data size, such as the items and users on a site, raises the stakes. The user's interests and prior item rating list were utilized to recommend items to the recommender system. In this paper, we discussed recommender system challenges: cold start, scalability, privacy, gray sheep, Shilling attack, Sparsity, Diversity, Prediction Accuracy, Inconsistency, Unpredictable Items problems. Also covered several study subjects and ways for overcoming Challenges. In future work, we will build a recommender system that will overcome the above issues.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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