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A Systematic Literature Survey on Recommendation System

Rashid Nadeem[1], T. Sivakumar[2]
[1, 2]Department of Computer Science, Pondicherry University, Puducherry, India

Abstract: For many applications, particularly in the academic environment and industry, the Recommendation System for Technical Paper Reviewers is very important. This study examines the research trends connecting the highly technical components of recommendation systems employed in various service fields to their commercial aspects. It is a technique that enables the user to identify the information that will be useful to him or her from the variety of facts accessible. In terms of the movie recommendation system, recommendations are made either based on user similarities in collaborative filtering or by considering the user's intended engagement with the content into account content-based filtering. A stronger recommendation system is produced by combining content-based and collaborative filtering, which overcomes the issues that collaborative and content-based filtering typically have. The similarity between users is also determined using a variety of similarity measures in order to make recommendations. We have reviewed cutting-edge approaches to collaborative filtering, content-based filtering, deep learning-based methods, and hybrid approaches in this study for movie recommendation. Additionally, we looked at other similarity measures. Numerous businesses, including Facebook, which suggests friends, LinkedIn, which suggests jobs, Pandora, which suggests music, Netflix, which suggests movies, and Amazon, which suggests purchases, among others, employ recommendation systems to boost their profits and help their clients. This essay primarily focuses on providing a succinct overview of the many approaches and techniques used for movie recommendation in order to investigate the field of recommendation systems research.
Keywords: Recommendation technique, Recommender system, Evaluation, Content-based filtering, Collaborative filtering, hybrid System

I. INTRODUCTION

A recommendation system is an informative tool that helps people find the products they want from the many products available [45][46]. A recommendation system's main goal is to forecast the rating a specific user will give a product. It helps the customer choose the best option from the available alternatives list. Recommendation systems are used by many companies, such as Netflix, Spotify, Flipkart, YouTube, Amazon, and others, to enhance customer service and boost revenue. Given that human preferences are constantly changing, it can be challenging to ascertain what a user wants from the resources offered, hence it is still an interesting research topic. These days, we purchase recommendations online. For instance, when we wish to buy books, online Shopping listen to music, view movies, etc., a recommendation system that runs in the background makes suggestions to the user based on his earlier behaviours [47]. Recommendation systems are used by many platforms, such as Netflix, which recommends movies, Amazon, which promotes purchases, Gaana, Spotify, which recommends music, LinkedIn, and Instagram, which recommends jobs, and any social networking site, which recommends members [48][49]. Users who use these recommendation engines can quickly find what they want based on their preferences. As a result, developing an effective recommender system is challenging because user preferences are always changing. The growth and adoption of the Internet and smart gadgets have greatly boosted traffic to websites, mobile apps, and social networking sites. Furthermore, these platforms are gathering more and more different types of information data that may be used to determine user preferences. Particularly, active usage of users' SNS platforms enables the collection of a variety of data, including information about the user's followers, tweet data, and material uploaded by the user. It is also simpler to gather various user-related exercise and bio related medical data thanks to the advent of wearable sensors linked to smart devices. Consequently, the Internet and smart devices have evolved into platforms for gathering numerous types of user data. In addition to user's click data (click stream) and implicit visit information data representing the user's behavioural patterns, such as records, can also be utilised by recommendation systems in addition to the explicit data directly provided by the user, such as likes and ratings, which were primarily used in the existing recommender systems. The use of implicit data in recommendation systems has lately expanded research on cognitive-based recommender systems, which look at users' personalities or behaviours to establish their preferences. This approach has the benefit of quickly updating recommendation systems to reflect changes in user preferences [50].

It is crucial to comprehend a user's preferences utilising different data mining approaches in order to use the user's explicit data and implicit data for item recommendations. As a result, research is always being done to improve the approaches for providing insights for suggestions based on the item's previous history, the user has chosen, feedback on the results of the recommendations, and correlation evaluation across users, among other things [1][3]. As a result, research is being actively done and broadened to enhance the efficacy of the recommendation system itself. It is required to filter the several item information offered by the service to recommender products that are tailored to consumers' likes or needs based on the findings of the data analysis. This filtering approach is comparable to the recommender system model. The field of research relevant to the recommender systems model was constantly developing and extending the bounds of the pre-existing models[50]. To put it another way, over the past ten years, research on sophisticated recommendation systems including data mining methods and recommendation models has exploded. These systems use vast amounts of data gathered in a multidomain environment to broadly understand user preferences and present more logical recommender to users.

On the other hand, although having a history dating back more than 29 years, recommendation systems have recently drawn attention due to the quickly growing market for streaming video content, highlighted by Netflix. This service sector analyses a large quantity of visual material, For the purpose of recommending films that fit the user's preferences, information data, user behaviour data, and user data similar to the users are combined. User satisfaction has gone up after this suggestion system was implemented in the streaming industry. As a result, Netflix is causing a change in consumer behaviour that is substitution or outpacing the consumption of current theatrical and TV-based media offerings[10]. Additionally, SNS platform-based services can gather several types of data, including social and evaluative data, and can make different recommendations. SNS data are being used in other service sectors to deliver services tailored to consumers' preferences. This has influenced various business improvements in service industries including travel and e-commerce in addition to improving the performance of suggestions. Interest in recommendation systems comes from both professional researchers and everyday users in the service sector that people interact with directly. The use of recommendation systems has developed, and research has been done to perfectly match the features of the service area. As a result, it can be said that the discovery of service sectors where recommender systems were reapplied and the interest in representative services that led to it was caused by a growing trend in the fundamental research pertaining to the recommender system. In this study, there are two methods for gathering data. first, look at the research and trends surrounding the recommendation model and technique. Second, high-reliability studies from a variety of studies pertaining to recommendation systems were carefully gathered and analysed for study on the recommendation service area. Since 2000, all the papers have been gathered using Google Scholar as the primary search engine with keywords like Recommender System, Hybrid Recommender System, Collaborative Filtering, Recommendation System, and Content-Based Filtering Additionally, this analysis is restricted to publications from the top 100 journals as well as databases from JSTOR, IEEE, ELSEVIER, ACM, and Springer. Conference papers, textbooks, Master's doctorate papers, unpublished papers, and news pieces were not included in the survey when it was being collected for this study. However, in the case of conference papers, papers from prestigious conferences including NIPS, WWW, IJCAI, AAAI, KDD, ICML, etc. were included in the analysis target after collecting, and finally, research was conducted using roughly 100 analysis targets papers. This research is structured with a focus on reliable publications that establish a link between the theory of the recommender system and helpful services. The quick procedure is illustrated in Fig 1.

Next, since 2000, publications containing the keywords "service application field" and "service recommendation" have been collected using Google Scholar as the primary search engine for Analysing the use of the recommended service's application trends. The number of papers that were published each year was then organised, and In order to analyse the relationship between research and application together, the scale or value trends of representative services in every service field were also observed throughout this time. This area's research was done to offer observation based on the full data field in order to analyse the overall direction of research and service fields, unlike the preceding section, This contained information from reputable journals. By comprehending the flow of a lot of research, By using these two study approaches, we intend to improve the precision of the primary contents connected to recommendation systems and serve as a platform for deciding the direction of future research.

II. BACKGROUND

A. *Problem Statement*

This recommendation engine suggests various movies to consumers. This system will deliver greater explicit outcomes in comparison to previous systems built on the content-based approach because it is based on a collaborative approach [39]. Content-based recommender systems are restricted to particular; they do not make general recommendations. These algorithms base their decisions on user ratings, which reduces your options for further exploration.

While our system, which is based on a collaborative technique, analyses the relationship between different clients and, based on their ratings, suggests movies to others who have similar tastes, so encouraging users to explore more [24]. It is a web application that allows users to rate movies and recommends films based on the ratings of other users.

B. *Solution Methodologies*

This section lays out the suggested system's strategy in several phases. The system's operation and the events that will take place are simply described below and with the aid of a flowchart in Figure 1.

1) *Step 1:* First, A screen with a search bar is shown to a new user, allowing him to look up a specific movie. If the user is already registered, a different screen will be shown to him.
2) *Step 2:* In this step, the user's local data, including the movies he is previously watched and the ratings he is given them, will be kept in a separate database.
3) *Step 3:* In this step, the user's local data, which includes the movies he has already watched and the ratings he has given them, will be kept in a separate database.
4) *Step 4:* In this step, A database called "Movie data" will store all the movie-related data (genre, summary, title, etc.), while a database called "User ratings" would hold all the user ratings from across the world.

III. SURVEY OF THE RECOMMENDATION CLASSES

First, recommendation systems are a helpful tool that can solve the issue of consumers being overloaded with information. It makes it possible to recommend products that are connected to the user, forecasts the grade of the items to be recommended to the user, and generates a list of user-specific recommendation rankings [13]. Many platform services employ a recommendation system to actively suggest tailored products that satisfy consumers' needs. To improve the effectiveness of these recommendations, research is being done on a variety of recommender systems filtering models and data mining techniques [39]. In this study, the entire flow of related research is analysed together with data mining approaches for the recommendation model utilised in recommender systems and their usefulness through research articles since 2010. summarises the analysis's main points regarding the recommendation model and technique. By classifying the primary service application fields where the recommendation system is used, showcasing the relevant research, and emphasising the primary service and relevant research trends, it is also feasible to grasp the overall organisation of the field of recommendation systems.

A. *Recommendation Models*

Recommendation systems were widely studied, used, and improved in a variety of academic and industrial domains. In the 1990s, a concept for collaborative filtering was originally developed. Recommendation systems are information filtering systems that provide a user's individualised product suggestions in a service environment that can store or collect various forms of data. Most often used in recommender systems, information filtering adapts to the user's behaviour or only proposes items that are assessed to be useful to the user [51]. Users enjoy having a large number of options, according to Iyengar et al. [52], and selection satisfaction declines as selection difficulty rises. This means that in order to increase a user's enjoyment with the recommendation system's service, it is required to suggest a variety of items to the user through the recommendation model in order to increase the user's choice of items. The user's implicit and explicit data, as well as the data of a group of users who are similar to the user, are analysed to produce a list of products that match the user's habits and traits, thereby reducing the selection overload.

Overview of recommendation models

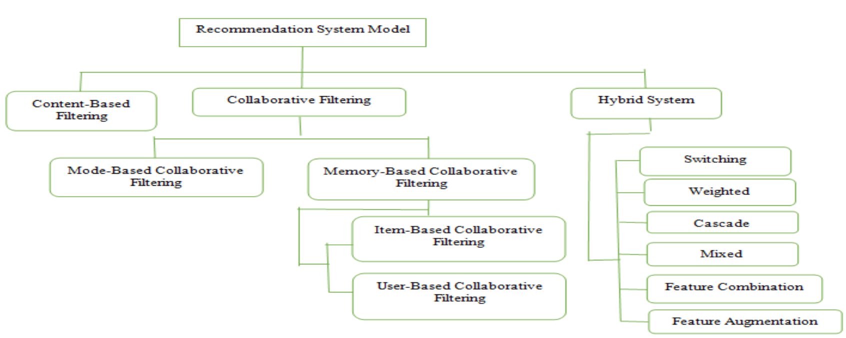

Fig. 1 Overview of recommendation models

Collaborative filtering was initially discussed by Wel et al. in 2017 [5]. The Tapestry system places too many demands on the user and only works for tiny user groups (such as a single unit). Tapestry offers a new recommendation as a prototype collaborative filtering, although it has various technical flaws.

Since then, news and On the basis of scores, collaborative filtering systems like Grouplens have recommended movies. Currently, numerous e-commerce websites, like Amazon, CDNow, Drugstor, and Moviefinder, among others, use the recommendation system. A vast amount of data is available. As we all know, in today's busy world, no one has the time to sift through millions of items to find one that suits their tastes.

Therefore, collaborative filtering is one way to sort the data and give the user relevant information. Collaborative filtering is one of the most well-known techniques for making recommendations. This technique relies on its user's recommendations on what their neighbours have made. Before producing the predictions, it determines how similar the user is to his neighbour. There could be n users.

This method searches the user list for comparable users. However, It is possible to establish whether two users are comparable based on the ratings that other users have given a particular item. The strategy is implemented in this way, and the desired result is achieved.

This tactic uses user ratings for any item in a sizable database of user-provided ratings for that particular item. User-item matrix is the name given to this extensive catalogue [26].

Item and User-based filtering have both been utilized in collaborative filtering by Ching-She Wu et al. [5]. In order to determine how similar users are, the authors employed Pearson correlation similarity. For the purpose of grouping N similar users together, another technique called Nearest N User Neighbourhood is used. The algorithm called Log Likelihood Similarity is used to determine how similar two items are. The Hadoop-distributed file system stores the results that the item-based recommender produces (HDFS). Yahoo Research Web Scope Database provided the dataset that was used in this study. Two additional categories of collaborative filtering are established. They are model-based and memory-based techniques.

1) *Memory-Based Method*: This approach is sometimes referred to as a neighbourhood-based strategy. Memory-based methods locate neighbours and produce predictions by using similarity metrics derived from explicit user ratings [26][31]. This kind of approach determines the user's interest in any given item. After analysing a user's perception of a given item, a similar user is checked to see if they share the same interests. Therefore, utility matrix analysis is used to identify similar users. In order to predict similar users, this type of technique mostly relies on the system's memory. Therefore, The unknown rating of any user can be constructed using the user-item rating matrix (utility matrix) if we can find comparable users. Finally, a suggestion can be made[48].

There are also two types of memory-based strategies. Approaches that are user- and item-based.

a) *User-Based Approach:* Using user-touser filtering is another name for this strategy. Using this technique, a rating matrix is created from n users and m things. In order to provide a suggestion for a new user, this method finds the closest neighbour using the neighbour's prior rating and offers a prediction for an item. Alternatively, recommendations are generated by searching for users with similar tastes [33]. Different similarity metrics or the creation of clusters can be used to identify similarities between people.
b) *Item-Based Approach:* "Item-to-item filtering" is another name for this method. Based on the ratings of related items, it is used to recommend any item. Only those items are eligible for suggestion after rating analysis identifies users whose ratings are comparable for various items [36]. It has been widely utilised by all major websites, such as Netflix and YouTube.

2) *Model-Based Method:* The model-based approach determines the projected value of unrated products by building a user model from each user's ratings [39]. To develop a model, this technique typically involves a data mining or machine learning algorithm. The rating matrix, which is constructed using user ratings for any item, is used in the model's development. The utility matrix is used to gather data for the model's training. To produce predictions for the users, Using the supplied data, this model is now being trained [46]. The model-based strategy is further divided into a number of groups. They include things like regression, artificial neural networks, decision trees, clustering, and association rule mining. There are many examples of model-based approaches in action. Some of them include matrix factorization, latent semantic techniques including latent semantic analysis, and singular value decomposition (SVD), and indexing as dimensionality reduction techniques. The sparsity issue that arises in recommendation systems is resolved using model-based techniques[42].

B. Content-Based Filtering

Content-based filtering is one of the most often used and researched recommendation classes (CBF) [24]. A crucial component of CBF is the user modelling process, which extracts user interests from the items with which users interact. Items often consist of text, such as emails or web pages. Usually, "interaction" is established through acts like downloading, purchasing, creating, or labelling anything. A content model that contains the features of the object is used to represent it. Typically, features consist of single words or phrases. Additionally, some recommender systems include non-textual components like XML tags, layout information, and writing style [21][6]. In most cases, only the most descriptive features often weighted are employed to model an item and its users. The most effective features are then kept, frequently as a vector that includes the features and their weights. The features of a user's possessions are often included in the user model. Using the vector space model and the cosine similarity coefficient, for example, the user model and suggestion candidates are compared to produce recommendations. Of the 62 reviewed techniques, 34 (55%) included the concept of CBF, making it the most common recommendation class in the research-paper recommender system field. Authorship [35], owning papers in one's collection, adding social tags [29], or downloading, reading, and browsing papers were typically the means by which people and products might "interact" with one another. Despite the fact that some of the reviewed approaches make use of n-grams, topics (words and word groups that appeared as social tags on CiteULike), concepts inferred from the Anthology Reference Corpus (ACL ARC) [34] via Latent Dirichlet Allocation, as well as concepts assigned to papers through machine learning, the majority of the approaches make use of plain words as features, with only a small number also making use of n-grams. Only a few methods make use of non-textual elements, and when they do, they usually combine them with words. Giles et al. weighted the citations using the common TF-IDF measure, using citations in the same way that they weighted the words in the text (i.e, CCIDF). The CC-IDF concept was embraced by others, or it served as a benchmark. The CC-IDF weighting technique, however, may not be perfect, according to some new data from Beel. The disadvantage is that content-based filtering consumes more computer resources than a stereotype. The features of each item must be examined, user models must be created, and similarity computations must be carried out. These calculations need a lot of resources if there are a lot of users and objects. The shortcoming of content-based filtering is that it overspecializes and lacks serendipity, which causes it to offer products that are as identical to those a user already knows as feasible. The quality and popularity of things are also disregarded by content-based screening [24]. For instance, if two research publications have phrases in common with the user model, a CBF recommender system might regard them as equally relevant. This connection may not always be supported, for instance, if one paper was written by a subject-matter expert who offers original findings while another was written by a student who summaries the findings of earlier studies. A CBF system would fall short of recommending only the first paper, as is ideal for a recommender system. The fact that content-based filtering is reliant on having access to an item's features is another criticism of it [26]. In order to make suggestions for research papers, PDFs typically need to be processed, translated to text, document fields detected, and attributes like words extracted. None of these jobs are simple, and they all run the risk of introducing inaccuracies in the advice.

C. Hybrid Filtering

This information filtering system uses user-submitted movie ratings as input before applying content-based and collaborative filtering to produce a list of suggested viewings [30]. It combines the two approaches of and content-based filtering. The idea of hybrid filtering comes into play when content-based or collaborative filtering alone is insufficient to address the problem. Adopting hybrid filtering can solve many problems with collaborative filtering and content-based filtering. Cold start problem is a fundamental challenge in collaborative filtering. Therefore, we might be able to solve the problem if we use collaborative filtering after applying content-based filtering. Therefore, making it hybrid can resolve the problem.

Darban et al. suggested a hybrid strategy that blends the idea of content-based filtering with genetic tags found in movie files [32]. Using the Principal Component Analysis with Pearson Correlation approach, it decreases the number of redundant tags to cut down on computing costs. Here It uses a dataset for movie lenses that was made available on October 18, 2016.

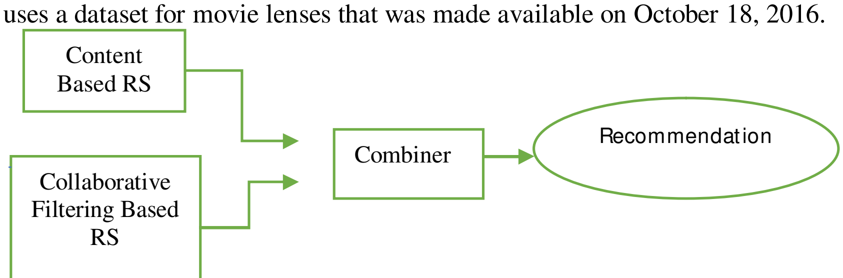

Fig. 2 Hybrid Filtering

To determine a user's likely choice, P. Ren et al. created a method based on hybrid features, such as user-supplied features, picture visual features, and converting user item evaluations into hybrid feature ratings [34]. The research presented here shows that the suggested method performs better on large datasets and yields better results on sparse datasets. A hybrid strategy based on social similarity and item attribute was created by Yang et al. in C. The collaborative filtering approach was combined by the author using social commonalities and movie genres. To address the sparsity issue, he used the BPR-MF model. The suggested process consists of two parts. Using the ratings from the training dataset, the BPR-MF model is utilized to first obtain the candidate set. The unknown ratings are forecasted using the present ratings once the candidate set has been found. The final candidate set for each user is collected once the ratings have been sorted. Each set has several top pieces. The user is provided with movie recommendations in the second step utilizing the feature selection TF-IDF technique, which measures the similarity between the user and the movie lens dataset. The results show that BPR-MF generates more accurate results than collaborative filtering. According to the methodology used by Priscila and J. Bobadilla in [53], To construct a single matrix model, they merged user reviews with demographic data such as age, gender, and occupation. Collaborative filtering is used to find ratings when they are missing. Enhancing the overall rating prediction is the main objective in this scenario. The datasets Film Trust, BookCrossing (BX), and Movie Lens are three separate ones (100k). Here, the performance of the suggested technique is evaluated using Mean Absolute Error (MAE). Using demographic information on the user and the object, the data sparsity issue is also resolved. R. D. and Bharti Gupta have created a system [55] that uses content-based filtering for inexperienced users and collaborative filtering for experienced users. In order to determine similarity, The author applied Pearson similarity and cosine. Information from the database about users and films is stored in Hadoop. The experiment makes use of the Movie Lens dataset.

Hybrid filtering can be divided into several categories. Understanding the figure below will help you comprehend hybrid filtering. As shown in the image, information is first subjected to both collaborative and content-based filtering; the outcomes of these applications are then blended to create hybrid filtering.

1) *Switching Hybridization:* The name implies that the recommendation technique is changed or switched. The system's current status is taken into account when switching is performed. To transition between the two recommendation systems, the system establishes the criteria. The purpose of this switching technique is normally to avoid ramp-up problems. However, both collaborative and content-based filtering have additional user issues. This approach was employed by a programmer by the name of Daily Learner, who first used collaborative and content-based filtering. [45] uses the switching hybridization method to alleviate several cold start problems. The author used both demographic-based CAMF-CC and content-based CAMF-CC to address the cold start issue.
2) *Weighted Hybridization:* In this hybridization technique, the system's list of suggested things is used to generate the first set of results for the recommended items. The P- Tango system, also called Personalized Tango, used this hybrid approach [45]. There is a database, a back end, and a front end in the P-Tango system. The back end downloads the articles and generates predictions, while the front end is accessed using a web browser. Typically, content-based filtering, collaborative filtering, and weighted hybridization are employed. In essence, weighted hybridization combines the predictions of content-based and collaborative filtering individually.
3) *Cascade Hybridization:* In order to enhance the recommender system, this technique generates recommendations using one technique and then filters or refines those recommendations using another technique. a technique for suggesting songs created by [37]. It Content Based RS Collaborative Filtering Based RS Combiner Recommendation performs as a middleware system, making digital audio/music collections more practical. To generate recommendations, collaborative filtering is used after content-based filtering. In response to the user's request, this system recommends tracks from the same genre. and uses collaborative filtering to consider both the preferences of previous users and other users. The collaborative, knowledge-based, and cascaded restaurant recommender EntreeC is also available.
4) *Mixed Hybridization:* As the name implies, it provides a lot of recommendations at once by using several recommenders. This mixed recommender is used when users want many recommendations at once. The Profiled recommender system [28], an agent-based website recommender system, is an example of a mixed kind. In order to identify user interests and lay the groundwork for collaborative filtering, ProbBuilder first collects information about site behaviours. Using both content-based and collaborative filtering, the user is then assisted in discovering pertinent pages of their choosing.
5) *Feature Combination:* Here, a few features are created by one recommender method at first, and later they are used by another. This method essentially blends content-based and collaborative filtering. This approach feeds a single recommendation algorithm with the attributes of many recommender systems. [37].

6) *Feature Augmentation:* Here, the results of one recommendation system are fed into another recommender system as input. Ratings and additional data from the second system are supplied into the first recommender system. The second system now uses this data and adds some further features to create suggestions [41]. Because it adds certain additional features to the initial recommender engine, feature augmentation performs better than feature combination.

D. Graph-based recommendation

Ten of the approaches that were assessed (16%) make use of the relationships that already exist in academia. The techniques construct graph networks based on these relationships, which typically display the links between papers created by citations [14]. Authors [30], users-clients, venues, genes, proteins, and the years that the papers were published are occasionally included in graphs. Lao et al. blended the graph technique with a content-based approach by including terms from the titles of the papers in the graph. The links in the graph can represent citations, purchases [57], authorship, gene relationships, or instances of genes in papers, depending on the articles in the graph. Some authors used non-inherent linkages to connect items. For instance, Woodruff et al. and Huang et al. determined text similarities between connected papers and items in the graph using text similarity [17]. Other linkages were made using cogitation power [33], demographic similarity, or attribute similarity [44]. After a graph was constructed, recommendation candidates were found using graph metrics. Typically, one or more input papers were provided, and the most popular elements in the graph were determined by conducting random walks with restarts from this input.

The literature survey discusses various methods for content-based and collaborative filtering. This subsection compares some of the most recent recommendation techniques, as revealed in the Comparative Study

TABLE 1
Overview of recommender systems surveyed

S.No	Authors	Year	Key Point	Description	Accuracy
1	Miyahara & Pazzani [1]	2000	CF, SBM	The authors developed a method to calculate a user's similarity between negative and positive user reviews independently.	Maximum classification accuracy of 71.6%
2	Thomas [2]	2004	CBF, latent semantic analysis	Collaborative filtering is a technology that is complementary to content-based filtering.	97.%
3	Adomavicius, & Tuzhilin[3]	2005	CF, rating estimation methods	The authors include descriptions of different limitations of present recommendation techniques as well as more adaptable and unobtrusive sorts of recommendations.	Not mention
4	Pimwadee & Lina [29]	2005	Supervised and Unsupervised Classification	The authors introduced studies the use of machine learning and semantic orientation for movie review mining.	The accuracy of mining 100 reviews from using semantic orientation approach was 77%, which was quite good. The recall rate for positive reviews was 77.91%, and that for negative reviews was 71.43%.
5	Ruslan & Andriy [16]	2007	RBM, SVD, CF	The authors introduced define a class of generalised two-layer undirected graphical models. Boltz-mann with restrictions machines for tabular or count data modelling.	Not Mention
6	Yehuda K. [8]	2010	CF	The authors propose a better strategy based on the idea of support difference, where min-sup is fixed for each item.	The Netflix Cinematch system could achieve a RMSE of 0.9514(= 95.14%).
7	Ghauth & Abdullah [4]	2010	CBF, eLearning, Peer Learning	The authors introduced compared to online courses using a content-based recommender system and online courses without one.	80%

8	Tommaso & Vito [19]	2012	Model-based RSs, SVM, Linked MDB	The authors introduced compare with other advisers both content-based and collaborative filtering systems methodologies.	CF Pearson=82.57%
9	Harald Steck [9]	2013	RS, RMSE	The authors introduced solving the ranking problem is useful for forecasting the rating value of any item.	RMSE=0.9224(94.24%) MAE=0.7215(72.15%)
11	Fatih & Dietmar [21]	2013	SVM, Cosine	The authors introduced innovative methods for determining and using context-specific tag preferences in the recommendation process.	Prec. (regress-tag-u_i = 83.90%) F1 (regress tag u_i = 83.30%) Recall (regress tag u_i = 82.73%)
12	Yi Cai & Ho-fung [24]	2013	CF, MAE, Neighbours Selection	The authors introduced comparison to other CF algorithms, CF recommendation strategies that improve the effectiveness of recommendations while using the movie lens Data sets take less time, especially when there are few training data.	
13	Sarwat & Levandosk [25]	2014	LARS, CF	The authors introduced LARS produces recommendations that are twice as accurate as currently used recommendation methods, according to both the Four-Square location-based social network and the MovieLens movie recommendation system.	MAE value is 0.8125 and coverage value is 0.9685 using TyCo
14	Xin & Mengchu [26]	2014	CF, NMF, Tikhonov regularization	The authors introduced the RSNMF's forecast accuracy depends heavily on the regularising coefficients.	89.15%
15	Rossetti & Stella [23]	2016	matrix factorization mode, Matrix factorization mode	The authors introduced the results from the online investigation with the same set of users significantly conflict with the ranking of algorithms based on offline accuracy measurements.	Accuracy statistics I2I = 43.8%, MF80 =50.4%, MF400 = 45.4%, POP = 34.00%
16	He & Chen [5]	2017	CF, CS	The authors introduced the user experience and trust in recommender systems can be greatly improved, and CS products can be promoted successfully, if the CS item problem can be solved.	prediction models for ICS movies (RMSE K=100) ALS= 1.124, SGD= 1.070, timeSVD++=1.053, CDL=1.179, IRCD-ICS=1.49
17	Ali & Nayak [6]	2018	CBF, Genome tags	The authors introduced in comparison to previous models, genomic tags provide the best results for detecting comparable types of movies and provide more precise and individualised suggestion.	Not Mention
18	Kim & Jeon [12]	2019	CF, RNN	The authors introduced applying the collaborative filtering process, we can compare the prediction accuracy of our modified RNN with that of the simple RNN	the accuracy of the cooperative filtering is 4.8%, the accuracy of the simple RNN is 11.5% and the accuracy of the modified RNN for similar user groups is 14.17%
19	Anwar & Uma [13]	2019	CF, Similarity Techniques	The authors introduced precision, recall, F1 score, and correlation measure-based rule mining are used to measure the correctness of recommendations.	Correlation = 95.3 Euclidean = 87.6 Jaccard = 85.3 Manhattan = 91.0 Cosine = 89.0

20	Sudhanshu & kanjar [7]	2020	CBF, RS, CF	The authors introduced with movie tweets, one may ascertain current fads, popular opinion, and audience reaction.	PLCC=76%
21	Fayyaz & Ebrahimian [28]	2020	Evaluation Metrics, CF, RS	This article provides review of the sorts of recommendation systems now available, along with their problems, restrictions, and commercial applications	Not Mention
22	Debashish & Chen [11]	2020	MF, DNN	The authors introduced the data recommended for the movie trailer Deep neural network models and matrix factorization are both used to increase accuracy.	RMSE (MF=81%, DNN=79%)
23	Arno & Karen [14]	2021	Knowledge graph, CAMF, CF	The authors introduced for technically speaking, sentiment-based knowledge graphs that recommend movies have been shown to be effective.	Integrating a knowledge graph improves both accuracy and interpretability
24	Dabrowski & Rychalska [15]	2021	EMDE, top-k, Session based recommendation	The authors introduced using EMDE in top-k and session-based recommendation settings, fresh cutting-edge findings on numerous open datasets in both unimodal and multimodal contexts are presented.	80%
25	Urvish & Ruhi [18]	2021	CF, RS	The author introduced Students, researchers, and fans will be able to develop more persuasive methods for MRS thanks to the combination of the extremely effective CF algorithm with other strategies.	The new item-based approach had MAE of 72.0% whereas the traditional item-based approach had MAE of 73.9%
26	Harald & Linas [20]	2021	NLP, RS at Netflix	The author introduced recommendations have eventually much improved as evaluated by both offline and online metrics thanks to deep learning.	Not mention
27	Khademizadeh & Nematollahi [27]	2022	CFA, Association rule	The author introduced numerous difficulties, including evaluation, collection acquisition procedures, and allocating funds for resources, could be addressed by applying analysis of the circulation data.	its training-set accuracy score was calculated for the loan duration of 82.5 and the frequency of renewals of 92%
28	Darban & Valipour [30]	2022	Deep learning Graph-based modelling, Autoencoder, Cold-start	The author introduced on recommendation accuracy; the technique (GHRS) performed better than several other existing recommendation algorithms. Additionally, the approach produced significant outcomes for the cold-start issue.	80%

The previous recommendation systems had certain gaps in them:

1) Because so many users choose not to rate items, the rating matrix is quite sparse.
2) The most prevalent issue with content-based recommendation is over-specialization.
3) Cold start is an issue that content-based recommendation systems always encounter.

Therefore, This motivates us to develop a new social model:

a) Improves sparsity by making rating compulsory.

b) Neighbourhood-based collaboration strategies are used to address the issue of over-specialization.

IV. CONCLUSION

The trend in recommender system models, after compiling research on recommendation systems from 2000 to 2022, the various technologies used in this area, and the business sectors adopting this area were examined in this study. First, the Content-Based Filtering recommendation model for the recommendation system, one of the earliest models to be employed, has steadily been used by itself. Additionally, it was found that, despite the fact that collaborative filtering research gained traction in 2014, research on hybrid systems that can supplement the advantages and cons of the Content-Based Filtering recommender system and the Collaborative Filtering recommendation model increased noticeably. However, depending on the service application industry, there are some situations when the usage of collaborative and content-based filtering is preferable. As a result, research should be done in relation to the research based on the application sector of service.

In this era, Recommendation systems are a highly common technology that serves to improve user and business experiences. Depending on how the system is developed by the developers, these systems can be content-based, collaborative, or hybrid. In this essay, we discuss various recommendation system types along with their benefits and drawbacks. Although content-based filtering techniques have significant drawbacks, they are advantageous for new users. The two categories of collaborative filtering methods are neighbourhood methods, which are used to suggest straightforward topics but are not accurate, and model-based methods, which enhance the quality of cold-start problems. Due to their many benefits, collaborative filtering systems are very popular. Hybrid solutions improve the outcome and increase the system's accuracy by overcoming the drawbacks of both content-based and collaborative filtering techniques.

In the future, On the basis of the results of this study, we plan to expand the scope of our research to look into and develop recommendation systems that are suitable for the characteristics of business by application service field.

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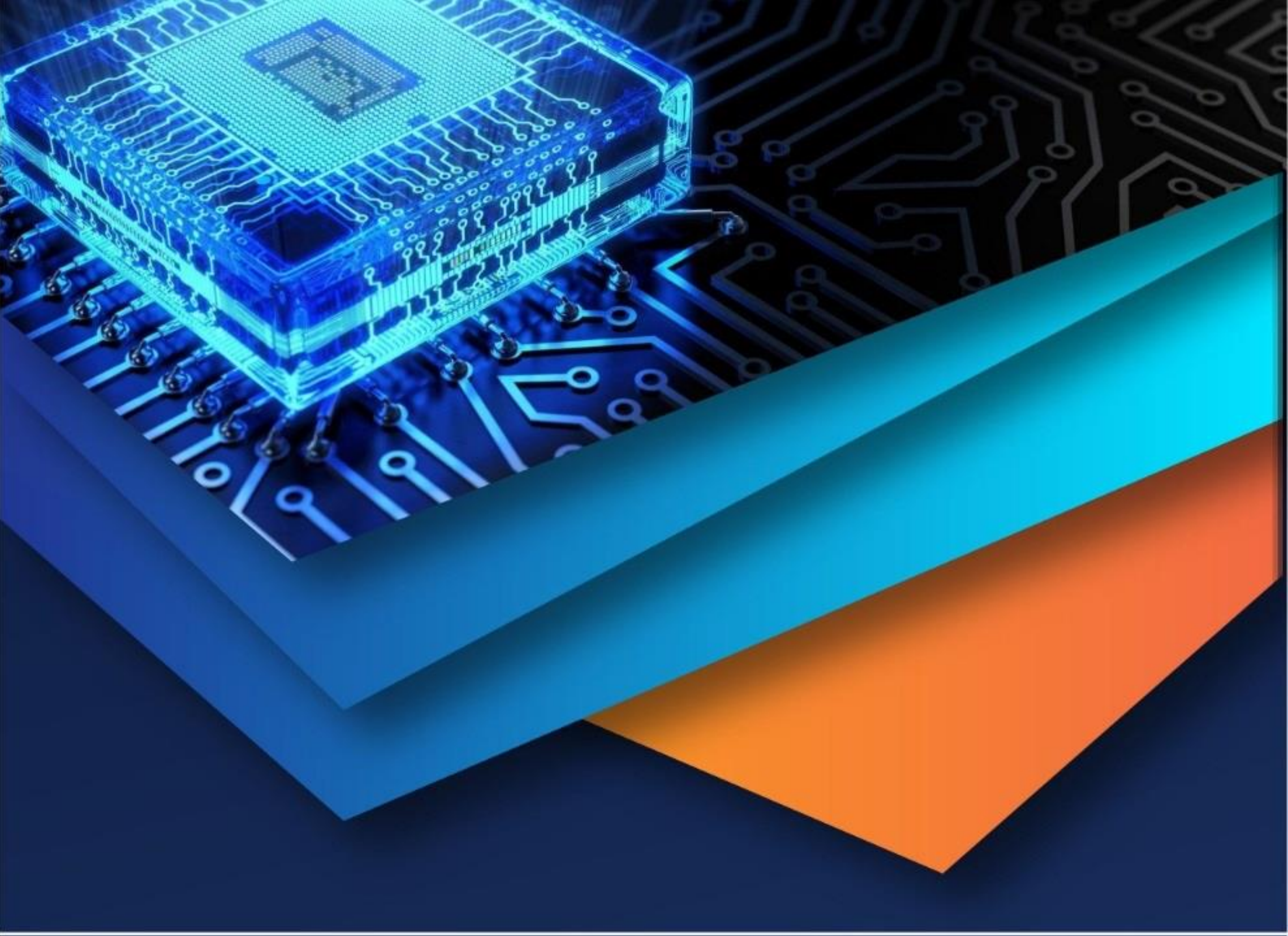

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