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Recommendation Systems: Types, Applications, and Challenges

Dhruval Patel[1], Foram Patel[2] and Uttam Chauhan[3]

[1]*Computer Engineering Department, Vishwakarma Government Engineering College, Gujarat, India*
[2]*Computer Engineering Department, Vishwakarma Government Engineering College, Gujarat, India*
[3]*Computer Engineering Department, Vishwakarma Government Engineering College, Gujarat, India*

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Abstract: Recommendation Systems help users select appropriate products or services from a wide range of choices. Thus, It solves the problem of information overload upto a remarkable extent. Specifically, It is highly applicable in certain industries that sell the product online or provide the services online. Recommendation Systems are very relevant in such a domain because they can grow their business by putting it in the practice. In this review article, we offer an overview of the Recommendation Systems and their variations and extension. We address the numerous techniques used for Recommendation Systems, including content-based filtering, collaborative filtering, sequential, session-based, etc. A comparison has been given for each technique for detailed analysis. It extends the review for the variety of dataset domains, such as movies, music, jobs, products, books, etc. Besides datasets, We have discussed various applications of the recommendation Systems across multiple domains in the industry. We survey various evaluation metrics used in a wide range of Recommendation Systems. In the end, we summarized the different challenges posed by the recommendation Systems, which helps make them more accurate and reliable.

Keywords: Recommendation Systems, Content-Based Filtering, Collaborative Filtering, Sequential and Session-based, Cold-Start, Machine Learning

1. INTRODUCTION

The explosive growth in the digital content over the Internet, and the billions of users of it, have created a significant information overload problem. As one of the consequences, it hinders timely access to items of interest on the Internet [1]. This situation has led to an increase in the demand for Recommendation Systems more than ever before. Recommendation Systems manage information overload problem by automatically recommending products or services for users that may suit their interests [2], [3]. Recommendation Systems(RS) have become an independent research domain due to its growing importance since the first attempt on collaborative filtering appeared in the mid-1990s [4]. The remarkable amount of work has been done to develop new methods for Recommending Systems not only in the industry but also in the academia over the last decade or so. Invention and advancements in the social network platforms in the recent time has led to an increase in the number of Internet users globally. Besides, online commerce attracts people to get the work done using a mouse click. The convenience offered to users by online business opened up the door of wide range of choices. As a result, it spreads rapidly all over the world. On the downside, Users faces circumstances in which they have so many choices available to choose from, where they need help finding and filtering out their likes and dislikes from the countless possibilities. Recommendation Systems comes here to rescue. The notion of personalized search engines and Recommendation Systems has been largely accepted by users who need help in searching, sorting, classifying, filtering, and sharing the plethora of information that is now available online [5]. Recommendation Systems are algorithms designed to recommend relevant items to users based on the similarity of items or user's profile characteristics. The phrase "relevant items" includes items to watch films and TV shows, text for reading, buying products or anything else[1] depending on the industrial sector [6].A Recommendation Systems must interact flexibly with the users for two reasons: first, to learn the characteristics and preferences of the user and second, to recommend items to users [6]. For example, Amazon is one of the major companies to deploy large-scale personalized recommendation model that makes recommendations to its users using various approaches to improve user experience [7], [8]. Several techniques have been proposed for the development of Recommendation Systems including Content-Based[9], [10], [9], Collaborative Filtering [11], [12], Sequential RS[13], [14], [15], [16], Session-based RS[17], [18], [19], [20], [21], [22], [23], [24], Graph-Learning RS [25], [26],

[1]https://towardsdatascience.com/introduction-to-Recommendation-Systems-6c66cf15ada

[27], etc. in various industrial and academic sectors.

A. Contribution of this paper

There are several surveys were performed on Recommendations Systems. They mainly discusses Principles, methods, evaluations and algorithms of recommendation systems [1], [28]. Besides, scholars have reviewed deep learning based RS [29]. However, there is still a absence of study of the RS research work keeping the viewpoint of datasets and implementation. we attempted to present a survey which primarily focused on datasets used, evaluation method and application domain. As per the best of our knowledge, in addition of study on various RS techniques, the RS exploration using the angle of datasets are the first try. It addresses various problems with their possible solutions inherent to all recommendation Systems. Besides, tt provides a comprehensive survey on various Recommendation Systems approaches that include Content-based, Collaborative Filtering, Session-based, Sequential, and some other various types. Also, it focuses on the implementation of the Recommendation Systems in real-world applications for various domains such as Entertainment, Tourism, Food, Health, etc.

The rest of this article has been arranged as follows. Section 2 studies the history and background of RSs. Section 3 portrays the different approaches used in RS. Section 4 briefs about evaluation techniques used in RS. In Section 5, a type of datasets and domains used in RS has been discussed. Section 6 represents a foresight on the traits and applications of future RSs as well the future research directions.

2. Background Study

Recommendation Systems assist people in the complex organizational environments to make the right decisions[30]. Nowadays, many information-based companies like Google, Amazon, Twitter, LinkedIn and Netflix utilize RSs[31], [7]. These Systems have played a crucial and indispensable role to bolster business and facilitate decision-making in various information access Systems[29], thus helping users to reduce risks[32] or to maximize the profits.

Extensive research has been performed on recommendation Systems with a multitude of publications in the last decade. The goal here is to study various novel approaches in the field of recommendation Systems. Most of the publications concentrate on Movie and Music RS, but there are many papers focused on the application of RS in different fields such as e-commerce, television, documents, e-health, e-learning, web search, books, news, and many others[33] [34]. For an instance, In [35], Chen et al. implemented a new strategy for e-commerce sites that takes into account the profitability factor along with the purchase probability and customer preferences to support both sellers and consumers. Two specific Systems are suggested based on this approach: CPPRS(Convenience plus Profitability Perspective Recommendation Systems) and HPRS(Hybrid Perspective Recommendation Systems), where the latter successfully boosts profit without compromising the accuracy of the recommendation. Yu et al. introduced a recommendation technique called user-profile merging for the recommendation of TV programs to multiple individuals watching TV together[36]. This technique merges all the user-profiles to create a common user-profile and based on this merged user-profile, the target audience will receive recommendations of the relevant TV programs. In [37], a personalized music recommendation Systems-MusicBox is proposed based on a combination of social tagging and audio features to provide users with accurate and tailored recommendations. The concept of an Intelligent Electronic Book Device solves the problem of information overload by recommending courses and educational materials depending on the interests of the student[38]. Based on the interaction of the user and the Systems, the authors considered different parameters such as favorite subject, session length, time to completion, etc. and attempted to improvise the user experience by making relevant recommendations. [39] developed a novel fuzzy linguistic recommendation Systems that implements a hybrid recommendation technique to help researchers find the right resources and explore knowledge in their field of study. This Systems also provides the user with an opportunity to meet other researchers of shared interests and collaborate on innovative research projects.

3. Classification of Recommendation Systems

A recommendation engine is a Systems that analyzes existing data to suggest something that might be of interest to an internet user, such as a document, video or work. Research scientists must select the right one from a handful of recommendation algorithms depending on the limitations and specifications of a particular industry or an organization. It is very important for a Systems to use reliable and accurate recommendation approaches which will provide useful and important suggestions to its users. Figure 1 depicts different recommendation filtering techniques offered.

A. Content-Based Recommendation Systems

Content-based recommendation Systems recommend the items based on the data that a user provides directly or indirectly. Analysis of documents / descriptions previously rated by the user is performed. Then a user profile is created based on that particular user's previous rating trends, which are then used for making recommendations. Content-based recommendation Systems is primarily used with applications of Information Retrieval Systems(IR) and Artificial Intelligence [3]. Content-Based uses the concepts of Term Frequency (TF), Inverse Document Frequency (IDF) and Cosine Similarity Matrix for the recommendation process. They are used to determine the relative importance of a document, article, news item, movie, etc [2]. Figure 3 depicts how Content-based recommendation works. This form of

[2]https://www.analyticsvidhya.com/blog/2015/08/beginners-guide-learn-content-based-Recommendation-Systems/,https://medium.com/kunalrdeshmukh/collaborative-filtering-in-recommendation-Systems-2fa49be8f518

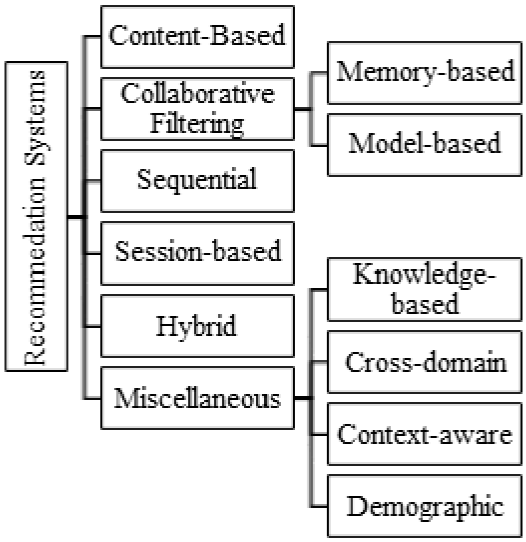

Figure 1. Taxonomy of Recommendation Systems

RS, as seen in the figure below, takes in an item that has been liked or purchased by a user in the past. The RS then analyzes the contents, category, and features of the purchased item to discover which other items have similar attributes. After that, based on the similarity scores, it recommends the most relevant item to the user[40].

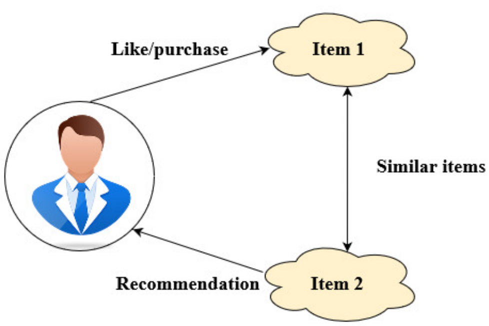

Figure 2. Content Based approach

Comparative Study

The Table 1 presents a comparison of the work of various authors in several papers on different datasets using content-based techniques for implementing the recommendation Systems. A total of three evaluation metrics are employed for comparison namely Precision, Recall, and F measure. High values of Precision and Recall are considered to be good indicators of an accurate model. F measure is the weighted average of Precision and Recall. From the table, we compared the recommendation model implemented in [41] on five subsets, out of which, high precision and recall values are obtained when implemented on MYST dataset, thus more accuracy is observed for this particular dataset, whereas the values are least on SF dataset. In [42] experiments are performed using Deep Learning (CNN) to develop a Content-based Image retrieval Systems on five distinct datasets. The performance of the Paris dataset having a higher precision value is better than the Oxford dataset. However, ImageNetILSVRC(2012) dataset does not seem to perform well. Comparing the work of Kompan et al. [43] for news recommendation with the experiment performed in [44] to develop CBRS using the graph indexing approach, the latter one yields more accurate results with very high values of precision and recall.

B. Collaborative Filtering Recommendation Systems

Collaborative Filtering(CF) is considered the most significant approach that is widely implemented in the industry, especially in e-commerce sites such as Amazon, Flipkart as well as online retail sites like Netflix for the promotion of their products and improvise its sales [46]. Developers at Xerox first use collaborative filtering in a document retrieval Systems. Google's Page Rank Algorithm is an example of a document retrieval Systems using Collaborative filtering [3]. CF methods in RS are based on the previous interactions between users and target items. These methods will require all historical data of user interaction with items as an input. Based on the past ratings given to the items by users, predictions would be made to the user [4]. Figure 4 shows the collaborative filtering technique used for the recommendation of various items. As we can see from the figure that since both users which liked purchasing the item1 were considered as similar by the RS. This similarity in item selection will by considered by RS while recommending next items to these users. So, when the right-most user selects item4 than this item will be recommended to left-most user due to their similarity in item selection in the past.

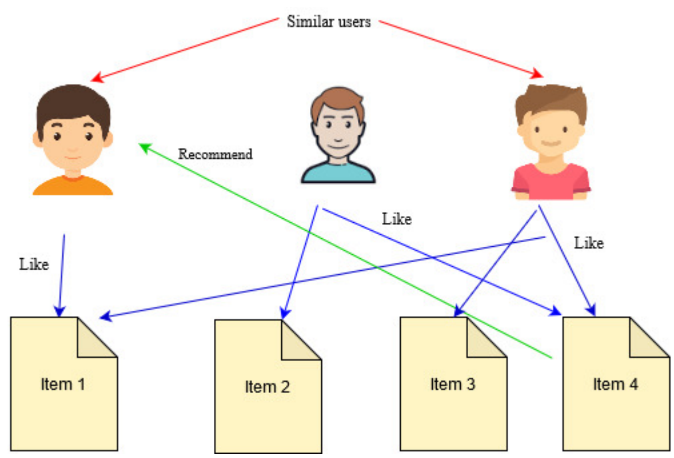

Figure 3. Collaborative Filtering approach

CF algorithms are further divided into two classes:

[3]https://medium.com/kunalrdeshmukh/collaborative-filtering-in-recommendation-Systems-2fa49be8f518

[4]https://www.kdnuggets.com/2019/09/machine-learning-Recommendation-Systems.html

TABLE I. Comparison among various Content-Based techniques

Author	Method	Datasets	Metrics		
			Precsion	**Recall**	**F-Measure**
Cami et al. [45]	Temporal Preference Model	MovieLens Dataset	0.76	0.18	0.29
Mooney et al.[41]	Text categorization	(Amazon dataset) LIT1	50.3	49.0	46.5
		LIT2	52.4	57.6	53.3
		MYST	82.1	83.4	81.5
		SCI	46.3	63.8	51.1
		SF	32.9	38.3	28.2
Wan et al.[42]	Deep Learning (CNN)	ImageNet ILSVRC(2012) (general image database)	0.3650	0.0028	-
		Caltech256 (object image database)	0.7748	-	-
		Oxford (landmark image dataset)	0.5273	0.2091	-
		Paris (landmark image dataset)	0.9200	0.0740	-
		Pubfig83LFW (facial image dataset)	-	0.330	-
Kompan et al.[43]	cosine-similarity search.	1000 articles from SME.SK news portal	0.165	0.202	0.182
Peng et al.[44]	Graph indexing approach	Manual dataset of 5000 photos	0.786	0.815	-

Memory-based method and Model-based method algorithms [47]. Memory-based algorithms are simpler as no model is required to be built. The algorithms used in these approaches are based on relationships between users (user-based) or items (item-based) and make recommendations by employing distance measurements, such as the nearest neighbor (K-nearest neighbor). Model-based algorithms utilize prediction models that are trained by the rating matrix of user preference data to produce recommendations. Examples of these algorithms are Matrix Factorization, Fuzzy Systems, Genetic Algorithms, Clustering, Bayesian Network, Singular Value Decomposition, Association techniques, Deep Learning Networks, and many more. CF suffers from various problems such as the Cold start problem, Data Sparsity, and Scalability problem.

Zhao et al.[48] have designed a user-based CF algorithm for the MapReduce framework and the algorithm is implemented on the Cloud Computing platform, namely Hadoop to solve the scalability problem and to improve the computational speed. Due to an increase in the use of Recommendation Systems on the net, a need arise for evaluating CF methods and measures that tests the quality of recommendations and the user's trust in these Systems.

Bobadilla et al.[49] have proposed a framework that gives certain importance to evaluate the novelty of the user's recommendations and trust in their neighbors. An equation is also provided in this paper that formalizes and unifies the CF process and its evaluation. Thus, a framework is designed using four graphs- Quality of Predictions, the Recommendations, the novelty, and the trust. One of the problems, CF algorithms suffer is data sparsity. Active learning algorithms are considered to be very effective in reducing the sparsity problem for Recommendation Systems.

Bobadilla et al.[50] have proposed a Bayesian Non-Negative Matrix Factorization(BNMF) technique as well as an original pre-clustering algorithm to improve recommendation Systems performance in the CF area as the tests performed on it provide rich results due to its high prediction accuracy and low execution times. BNMF method is very useful as it is not only flexible, accurate but also improves the performance.

1) Memory-Based Algorithms

Memory-Based Collaborative Filtering approaches can be split into two main sections: user-based collaborative filtering and item-based collaborative filtering. User-based filtering takes a single user, identifies users similar to that user based on rating similarities, and recommends items that those similar users liked [5]. By contrast, item-based filtering finds users who liked an item and searches for other items they or similar users also liked. It then recommends other items based on those items. To calculate the similarity between item/user, various types of similarity measures are used. The two most common similarity metrics are the Pearson correlation coefficients and the Cosine-based measure.

Although the memory-based techniques are easy to implement, as the size of the dataset would increase, the online performance of recommendation Systems tends to decrease whereas the online performance of model-based algorithms is better than memory-based algorithms [46].

2) Model-Based Algorithms

Bayesian Networks In Bayesian networks, variables and their conditional dependencies are represented as directed acyclic graphs (DAG). In DAG each edge corresponds to a conditional dependency and each node corresponds to a unique random variable [6]. They are used for a broad range of tasks that are distributed among four major analytics disciplines namely: Descriptive analytics, Diagnostic analytics, Predictive Analytics, and Prescriptive analytics [7]. Bayesian Networks provide an easy way to represent the potential relationship among data through DAG and serve as a powerful tool for the creation of personalized recommendation Systems. Bayesian Networks uses Bayesian Inference for probability computations.

Using Bayesian Networks, Zhang et al.[51] have developed an online personalized recommendation engine. The model employs partial ordering relations as foreknowledge and realizes online structure learning and uses a correctional function for online parameter learning. Inference derived from Bayesian Networks are used to provide appropriate and accurate results to the querying users in recommendation Systems.

Yang et al.[52] have proposed a Bayesian-inference based recommendation algorithm for online social networks. They have employed a movie recommendation as an application to illustrate their algorithm. Based on the query responses and rating history, a Bayesian Network is built which is used as a basis by the proposed algorithm to calculate a recommendation rating to the querying user.

Clustering Clustering is the task of dividing the set of objects or data points into several groups(called as clusters) such that data points in the same groups are more similar to other data points within the same group than those in other groups [8]. The data points in the same cluster have some common characteristics. Clustering has an incredibly wide range of applications such as Anomaly Detection, Social Network Analysis, Recommendation Systems, Market Research, Image Segmentation, Search Result Grouping, Medical imaging, etc [9]. Various Clustering Algorithms such as K-Means, Hierarchical Clustering, etc have been widely used in building recommendation Systems for various applications as this approach divides a large dataset into smaller clusters that are easy to study and process[40].

Li et al.[53] have employed the K-Means Clustering algorithm to group the movie items by using the item-attribute – movie genre out of various other attributes. They have suggested a technique called ICHM(Item-based Clustering Hybrid Method) which introduces the contents of items into the item-bases CF to improve its prediction quality and solve the cold-start problem. Pham et al.[54] have also presented a clustering technique that is employed on the social network of an active user to find the communities of similar users and use these communities as a mechanism to make recommendations to the active user.

Matrix Factorization Matrix Factorization is a Collaborative based filtering method that works by decomposing the user-item interaction matrix into two lower dimensionality rectangular matrices. The decomposition is such that the multiplication of two lower dimensionality matrices will give us the original matrix. MF is used for performing complex matrix operations and most importantly for discovering latent features between two different entities [10]. MF is used in various domains such as in image recognition, recommendation Systems, etc. MF is widely used in building many real-world recommendation Systems as it gives a more compact representation than learning the original matrix P (of dimensions a*b), the reason being the original matrix P with a*b entries is difficult to study than the two lower dimensionality matrices Q and R of dimensions a*c and c*b respectively which have total (a+b)*c entries.

In Recommendation Systems MF is employed by representing the users on one dimension of matrix and the items of interest on another dimension of the matrix, the resultant matrix is filled with input data which the Recommendation Systems relies on. MF enables extra data to be incorporated. For example, Recommendation Systems can use implicit feedback when explicit feedback isn't available, which infers user preferences by observing the user's purchase history, browsing history, search behavior, or even mouse movements [55]. Mnih et al.[56] have presented a Prob-

[5]https://towardsdatascience.com/various-implementations-of-collaborative-filtering

[6]https://towardsdatascience.com/introduction-to-bayesian-networks-81031eeed94e

[7]https://www.bayesserver.com/docs/introduction/bayesian-networks

[8]https://www.analyticsvidhya.com/blog/2016/11/an-introduction-to-clustering-and-different-methods-of-clustering/

[9]https://en.wikipedia.org/wiki/Cluster_analysis#Applications

[10]https://medium.com/@paritosh_30025/recommendation-using-matrix-factorization-5223a8ee1f4

abilistic Matrix Factorization (PMF) model which scales linearly with the number of observations and performs well on very sparse and imbalanced datasets, such as the Netflix Dataset which contains over 100 million movie ratings.

Neural Networks Neural Networks(NNs) are a member of Machine Learning techniques that are implemented to model complex relationships between inputs and outputs. They also help to find patterns in data through a process that works similarly to the human brain's neural network. NNs can adapt to the changing input; so the network induces the best possible result without needing to reconstruct the output criteria [11]. When it comes to artificial neurons, NNs are also called artificial neural networks (ANNs), which constitute a network of interconnected artificial neurons using a mathematical model for information processing based on connectionist theory [12]. They consist of three types of layers: input layer which receives input data, hidden layer used for computation and output layer to receive output. Neurons that are interconnected with each other are aggregated into layers. The information received at each neuron is processed and is transferred to the other neighbouring neurons by edges or connections. Different types of NNs are Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), etc. NNs are extensively used in speech recognition, business analytics, social network filtering, medical diagnosis, etc. NN embeddings are used in the recommendation Systems to find entities that are close to one another in embedding space which allows us to find the most similar categories of entities among thousands of available choices.

Hidasi et al.[19] have proposed an RNN based approach for session-based recommendations. They have dealt with the issues that arise when modeling sparse sequential data and introduces modifications to classic RNNs such as new ranking loss function suited for training these models. Covington et al.[57] have proposed an architecture comprised of two deep neural networks: one for candidate generation and one for ranking, for recommending YouTube videos. Their deep CF model is able to effectively assimilate many signals and model their interaction with layers of depth, surpassing past MF approaches used at YouTube.

Association Rules Mining Association rule mining(ARM) is a rule-based machine learning method that is meant to find frequent patterns, relationships, associations or causal structures from data sets in various kinds of databases such as transactional databases, relational databases, and other forms of data storehouse [13]. One distinct feature of ARM over CF is that association rules do not extract an individual's preference, but rather finds relationships between set of elements of every distinct transaction [14]. The aim of association rule mining is therefore to seek rules that allow us to predict the occurrence of a particular item based on the occurrence of the other items in the transaction. Major applications of association rules are in market-based analysis, cross-marketing, Web usage mining, intrusion detection [15], Catalog design, etc. Association rules mining can be effectively used in building various recommendation Systems because of their ability to seek rules that govern the relations between variables in large databases, which then form the basis for making recommendations.

Mobasher et al.[58] have presented a scalable framework for Recommendation Systems using association rule mining from clickstream data. In their proposed framework recommendations are generated based on matching the current user session against patterns discovered through association rule mining on user transaction data. In their work, they have used the Apriori algorithm. Their Apriori algorithm utilizes a data structure(which is used to store frequent itemsets), to generate recommendations without first generating all association rules from itemsets.

Sobhanam et al.[59] have proposed a solution to cold start problems (arising in various recommendation Systems) by combining association rules and clustering techniques. In their work, they have created and expanded the user profiles using association rule technique, so that it will contain more number of ratings which solves the new user problem. The results obtained by applying the association rule technique are used in the next phase which is clustering.

García et al.[60] have described a Recommendation Systems that uses interactive iterative association rule mining and CF in order to help teachers maintain and constantly enhance e-learning courses. The ARM algorithm has been implemented that combines two different algorithms: 1)Predictive Apriori for discovery of association rules without parameters, and 2)IAS for the subjective comparison of unanticipated rules with a knowledge database on the field described earlier.

C. Comparative Study

In the Table 2, we compared the experimental results of several research works,where the researchers have employed collaborative-filtering based recommendation methods. We have taken RMSE(Root Mean Square Error) value as a metric for comparision between these works. The recommendation filtering Systems with lower RMSE values have the highest recommendation accuracy. From the above table, it is clear that the experiment conducted on the Flixster dataset using the DLMF method suggested by [61], shows the results of recommendations with the least RMSE value. It can also be inferred from the table that if we disregard the absolute error values of a given RMSE value then it can be deduced that the experiment carried out on the corel5K dataset using the FBS method suggested by [62] indicates the effects of recommendations with the highest RMSE values. By comparing the RMSE values of

[11] https://www.investopedia.com/terms/n/neuralnetwork.asp
[12] https://en.wikipedia.org/wiki/Neural_network#Applications
[13] https://www.techopedia.com/definition/30306/association-rule-mining
[14] https://towardsdatascience.com/association-rules-2-aa9a77241654
[15] https://en.wikipedia.org/wiki/Association_rule_learning

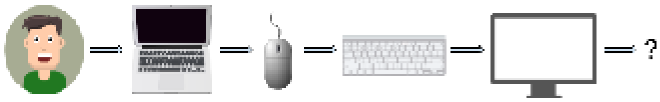

Figure 4. After buying a macbook, a mouse, a keyboard and a computer monitor, what would Mike buy next?

any method proposed by [46] with any method proposed by [63], it can be concluded that MESVD and ESVD methods possess the least RMSE values, but the datasets used by both are not fully the same as the MESVD and ESVD methods are employed on a subset of the full Netflix dataset whereas the IRCD-CCS and IRCD-ICS methods are employed on the full Netflix dataset. In the experiment performed by [64] the proposed DNN model has the least RMSE value when employed on the MovieLens-1M dataset.

D. Sequential Recommendation Systems

Sequential Recommendation Systems (SRSs) have been at the forefront of RS research in recent years because they deliver more intelligent and desirable recommendations to fulfill our daily needs. Traditional RSs used Collaborative filtering and Context-based techniques, which were unquestionably successful. In some circumstances, however, it ignores the hidden intricate relationships in user-item behavior. Due to this constraint, researchers have begun to shift their focus to Sequential RS, a more sophisticated notion in RS that includes Session-based recommendation, next-item prediction, next basket recommendation, next action recommendation, and so on [68]. When predicting the next item, SRSs use the user's long-term preferences as well as previous recommendations [16]. This requires that the SRS's input data be either chronologically organized or contain time-stamps, so that this organization may be considered when making recommendations [69] [70].

The Markov chain model was used to introduce the first sequential RS [71] [72]. Then, as the field of deep learning progressed, multiple CNN-based models were started to be used to generate sequential recommendations [73] [74]. Attention-based Sequential RSs were also recently presented [75] [76] [77]. Figure 4 depicts the sequence of purchase of relevant items. SRSs recommend items that may be of interest to a user by primarily modeling the sequential dependencies across user interaction. In reality, users' shopping behaviors are more likely to occur in a sequential order than that in random order. As an example, consider Mike's purchasing activities represented in Figure 4. Mike first purchased a Macbook, followed by a Mouse, a Keyboard, and a Computer monitor. It is possible that his next purchase will be a pair of Airpods. In this case, each of Mike's subsequent acts is contingent on the previous ones, making all four consumption actions sequentially reliant [16]. Such sequential dependencies are frequent in market data, but these are difficult to identify with traditional content-based RSs or collaborative filtering RSs, which is why SRSs were developed.

A typical example of SRSs is the Next Basket Recommendation. Basically, Next Basket Recommendation (NBR) is a strategy in which a user purchases a group of items (a basket) at a specific time, and NBR then uses the baskets to do sequential modeling and generate personalized recommendations. In [78], Tong et al. proposed a new Deep Learning-based Next basket recommendation model. They developed an attribute-aware multi-level attention mechanism that takes into account both long-term and short-term user preferences, as well as the relationship between the items in a basket. In this way, a more advanced method of recommendation is used to offer trustworthy and personalized results.

E. Session-based Recommendation Systems

Session-based Recommendation systems operate algorithms to furnish users with recommendations based on their most recent interactions during the current session. Interactions can refer to a variety of things, including the user's browsing history, click behavior, access time, and so on. Each user session has a purpose depending on his or her domain of interest, and the time frame for each session can change [22]. However, unlike other recommendation systems, they do not consider users' past preferences (outside of the current session) the majority of the time. They've grown in popularity for a variety of reasons. Two major significant causes are: First of them is users' selection of items is influenced not only by long-term historical preferences, but also by short-term and most recent preferences, and the second is that users aren't always signed in when browsing a website, making it impossible to track their past activity. Session-based recommendation systems have a wide range of applications, including Music Recommendations, Rental Recommendations, Product Recommendations, and so on, according to [79].

Recurrent Neural Networks (RNNs) have been utilized in various studies to make session-based recommendations. Works such as [23] and [19] illustrate the usage of RNN for session-based recommendations and ways to outperform commonly used approaches. When dealing with session-based recommendation systems, further studies have also focused on the problem of missing historical data. Massimo et al. have tackled this problem by devising a novel technique that can handle both cases: 1) when user data is propagated between sessions and 2) when information from previous sessions is unavailable. Some session-based recommendation systems are vulnerable to the cold-start problem because they lack access to past session information. The authors of [21] addressed the issue of cold-start by considering the content of items that will be recommended to users. In their paper [24], Massimiliano et al. have also addressed this issue in order to make better recommendations at the start of the user session (i.e. when there is not enough user preference available). A recent study [20] built a framework that overcomes the limitations of earlier Session-based Recommendation Systems to deduce users' overall interests.

TABLE II. Comparison among various CF based approaches

Author Name	Dataset Used	Proposed Method	RMSE (Root Mean Square Error)
Deng et al.[61]	Flixster	DLMF	0.7853
Guan et al.[46]	Netflix	MESVD ESVD	0.9248 0.9265
Jamali et al.[65]	Flixster	SocialMF	0.815
Rao et al.[66]	MovieLens	User-Based CF	1.022968896
Wei et al.[63]	Netflix	IRCD-CCS IRCD-ICS	1.053 1.048
Xu et al.[67]	Ciao	TUCross(trust) TUCross(no trust)	1.0237 1.1285
Guo et al.[62]	corel5K	CBS FBS	1.89 ± 0.02 1.90 ± 0.02
Zhang et al.[64]	MovieLens-100K MovieLens-1M Epinions	DNN model	0.9874 ± 0.0291 0.9357 ± 0.0151 1.2405 ± 0.0344

F. Hybrid Recommendation Systems

Many problems arise in RS such as Cold-start problem where the recommendation for new items is difficult to provide as no previous ratings or training data for those items are available. Other issues like Data Sparsity and Scalability are also faced by the recommendation Systems that result in very poor quality and inaccurate recommendations. Content-based Systems can recommend ”cold-start” items but the accuracy of the recommendation provided is low as compared to CF approaches. On the other hand, CF-based Systems provide accurate recommendations but fail on the Cold-start problem and Data Sparsity problem. Each of these RS techniques has its strengths and weakness. Thus, as shown in Figure 5 a Hybrid approach is developed to combine these different kinds of information from individual RS techniques to solve the problems and yield better recommendation results [80], [81]. Netflix is a good example of the use of hybrid Recommendation Systems. The website makes suggestions by comparing the viewing and browsing patterns of different users (collaborative filtering) and by offering films that share features with films highly rated by the user (content-based filtering) [16]. Robin Burke in his earlier survey identified the following 7 types of Hybrid Recommendation techniques [82], [83]:

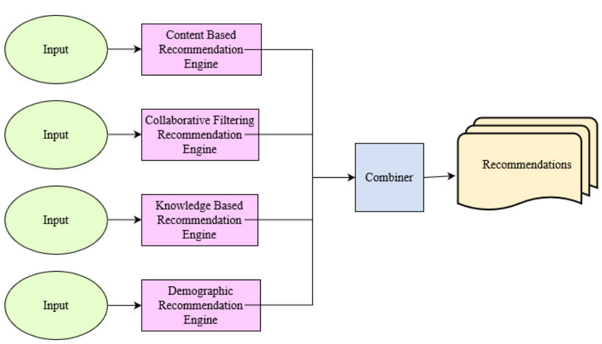

Figure 5. Hybrid approach

[16]https://en.wikipedia.org/wiki/Recommendation_system

1. Weighted: The scores(points) of various recommendation techniques are merged to generate a single recommendation [84].
2. Switching: The Systems switches among different recommendation techniques depending on the situation and applies the selected one.
3. Mixed: Recommendations from various Recommendations are presented together at the same time.
4. Feature Combination: Features extracted from different data sources are combined and passed into a single recommendation algorithm.
5. Cascade: One Recommendation attempts to the recommendations provided by another [85].
6. Feature Augmentation: One recommendation technique in the Systems is used to generate an output, that output is used as an input feature to another recommendation technique [86].
7. Meta-level: Some recommendation techniques are applied and produce some sort of model, which is used as input by another technique.

G. Comparative Study

The Table 3 compares the work of different authors in five distinct papers over multiple datasets by employing the Hybrid based recommendation Systems. The evaluation metric that is to be considered for comparison is Mean Absolute Error(MAE). Lower the MAE values, the higher the model’s accuracy. From the table above, it can be inferred that the Hybrid Recommendation Systems(RS) developed in [87] shows the least MAE value with less computation time. Whereas, the experiment conducted in [88] on the FilmTrust (FT) dataset gives the highest value of MAE indicating that the RS has the least accuracy. Further, on comparing the two versions proposed in [89] for a Movie recommendation Systems, the substitute hybrid recommendation model provides higher accuracy than switching hybrid recommendation model. The experiment conducted in [90] has the least MAE value when employed on the Last.fm dataset, however, this MAE value is higher than the value of the model proposed in [91].

H. Miscellaneous Methods

Knowledge based - This type of recommendation Systems makes use of knowledge about users and items to produce a recommendation rationalizing which products meet the user's requirements. The Systems will measure the similarity between the user profile and items in the item database to determine which items are better matched to the users and then recommendations are given to a user [92], [93]. Here, the user profile is inferred from the examples provided by the user based on their requirements. In comparison to CF and CB, Knowledge-Based Recommendation Systems do not encounter a cold-start problem[4] because their recommendations are related to domain knowledge instead of ratings. For e-learning materials[94] have suggested a knowledge-based personalized Recommendation Systems, wherein ontology is used for representation of knowledge. Similarly,[95] suggests a knowledge-based recommendation Systems to assist educators in the design of teaching-learning activities, assisted by an ontological modeling approach. The key downside to such a recommendation Systems is the requirement of knowledge engineering skills[82].

Cross-Domain- Many Recommendation Systems work on a particular domain. Such Systems suggest products related to the same domain where users gave rating [96]. The incorporation of various domains into one recommendation Systems called the Cross-Domain Recommendation, will allow users to cover various types of items[97], [98]. In a target domain, Cross-Domain Recommendation Systems (CDRS) will provide recommendations based on the data collected from a particular source domain. In simple terms, to enhance the quality of recommendations for the items in the target domain, the CDRS will take advantage of the information about users and items in the source domain. A cross-domain Systems, for example, needs to be able to recommend movies or books to users who only have given their musical preferences. There are two key points that motivates the concept of CDRS. The first point refers to addressing the common Cold-start problem which is faced by most of the recommendation Systems. In many RSs, there are often no user ratings or any useful information about the users available in the target domain, although the source domain may contain a large number of ratings from those users. Such ratings/data from the source domain can then be used in the desired domain to make recommendations. CDRS can thus be used to tackle such problems. Second, CDRS can be used to recommend a bundle of related items from different domains to a particular user[99]. Thus, it is crucial to examine the similarities between user ratings across various domains to find such desirable bundles.

Context-Aware - The simple fact is that users interact directly with the Systems within a specific context, and in one context the preference for items may vary from those in another. Context-Aware Recommendation Systems(CARS) provide very relevant recommendations by adjusting them to the specific sense of the user's situation [100]. Here, the recommendations provided depend solely on the contextual setting of the user details [34], [101]. Hence, considering both user and contextual information in a recommendation process can be beneficial for recommending various items. A scalable large-scale context-aware RS is been proposed by [102], which does not suffer from cold start problem. Their solution to the cold start problem is to use an adaptive item clustering algorithm. The applications of context-aware RS have been explored in numerous fields such as movies[103], music[104], [105], social rating services[106] and mobile recommendations[107]. Performance comparison of different pre-filtering, post-filtering and contextual modeling context-aware RS methods has been done by [108]. They have also identified 3 primary factors influencing the performance of these approaches: the type of recommendation task, the granularity of the context and the type of dataset.

Demographic - Recommendations produced with demographic filtering are based on the demographic profile of a consumer. The recommendation here focuses on information about users that is related to a demographic feature such as nationality, age, gender, etc[109]. A demographic approach has the advantage that, unlike collaborative and content-based recommendation techniques, this does not require a background of user ratings or knowledge of the item and can thus solve the cold-start problem . On the other hand, demographic Recommendations have the problem of acquiring the required demographic information of users in order to make reliable recommendations as most users are reluctant to share any of their personal data online. In [110], the demographic approach is to recommend restaurants based on user demographic information such as age, gender, etc. as well as restaurant ratings. Here, the user information is gathered by examining the HTML home pages of all users and using text classification to classify them. In other words, the home page of the user will be used as a positive example if a user likes a specific restaurant and when a user dislikes a restaurant, it will be considered a negative example. After that, to learn the characteristics of home pages linked to users who gave positive ratings, the author used the Winnow algorithm. Although the performance is not very good, it can be improved by integrating the demographic data with the other data available. Therefore, demographic Recommendations are often used in the hybrid approach, where the advantages of this concept are used efficiently to generate accurate recommendations.

Out of all the RS-related papers which we reviewed the majority of the papers used CF-based approaches for their experiments. Miscellaneous methods were the second most popular among the articles reviewed whereas CB based methods were the least used for applications. Figure 6 depicts the distribution of papers among 4 categories of RS namely: CB, CF, Hybrid, and Miscellaneous.

TABLE III. Comparision among different Hybrid methods employed

Author	Datasets	Values	
		MAE	Computation time(s)
Lekakos et al.[89]	MovieLens + IMDb (Switching version)	0.7501	16
	MovieLens + IMDb (Substitute version)	0.7702	10
Thong et al.[87]	The benchmark medical diagnosis dataset namely HEART from UCI Machine Learning repository (University of California, 2007) consisting of 270 patients characterized by 13 attributes.	0.395	2.68
Kouki et al.[90]	Yelp Academic Dataset	0.917	-
	Last.fm	0.833	-
De Campos et al.[91]	MovieLens + IMDb	0.7198	-
Ghazanfar et al.[88]	MovieLens(ML)	0.696	-
	FilmTrust(FT)	1.341	-

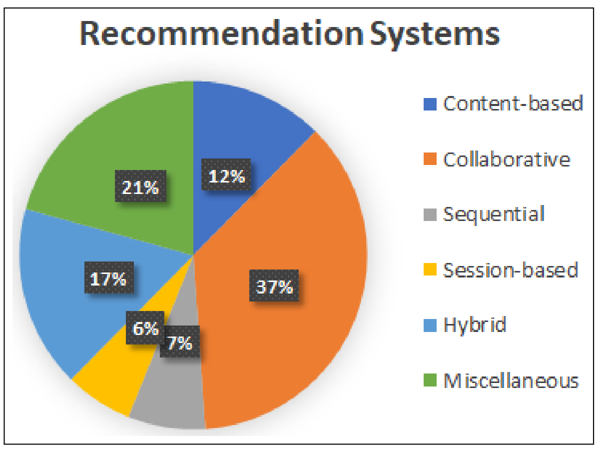

Figure 6. RS categories proportion

4. Evaluation metrics

Evaluation of predictions and recommendations has become important since research into RS started [111], [12]. Research in the field of RS requires quality indicators and performance measuring standards to know the quality of the recommendation techniques, methods, and algorithms [112]. The type of metrics employed depends on the filtering technique [1]. It also depends on the features of the dataset and the type of tasks that the Recommendation Systems will be performing [113]. The most commonly used evaluation metrics are:

- Mean Absolute Error(MAE)- MAE is the most commonly used evaluation metric; it is a measure of recommendation from the user's actual value. The lower the MAE, the more accurately a user ratings are predicted by the recommendation engine. It is computed as follows [1]:

$$MAE = \frac{1}{N}\sum_{u,i}|p_{u,i} - r_{u,i}| \tag{1}$$

- Root Mean Square Error(RMSE)- RMSE is a statistical accuracy metric that puts more emphasis on larger absolute error [1]. RMSE is more responsive to aberrations or poor predictions. RMSE is by definition never going to be as small as MAE. The lower the value of the RMSE metric, the more accurate the recommendation results. It is computed as follows [61]:

$$RMSE = \sqrt{\frac{\sum_{u,i}(R_{u,i} - \hat{R_{u,i}})^2}{N}} \tag{2}$$

- Precision- Precision is the proportion of relevant recommended items out of the total number of recommended items [33]. It is computed as follows [1]:

$$Precision = \frac{Correctly\ recommended\ items}{Total\ recommended\ items} \tag{3}$$

- Recall- Recall can be defined as the fraction of relevant items that also belong to the list of recommended items. It is computed as follows [1]:

$$Recall = \frac{Correctly\ recommended\ items}{Total\ useful\ recommended\ items} \tag{4}$$

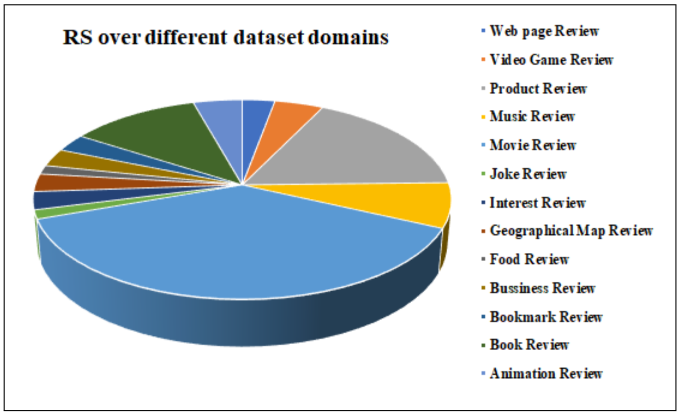

Figure 7. Recommendation Systems over various datasets

- F-measure- F-measure is a metric that combines precision and recall into a single metric. It is computed as follows [1]:

$$F - Measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (5)$$

TABLE IV. Performance metrics used in papers reviewed

Metrics	Papers
Precision	[45], [41], [42], [43], [44]
Recall	[45], [41], [42], [43], [44]
F-measure	[45], [41], [43]
RMSE	[61], [62], [46], [64], [63], [65], [66], [67]
MAE	[89], [88], [87], [90], [91]

5. Datasets and Domains

There is a significant range of varieties of the datasets used for recommendation system. In this section, we study the broad categories of the datasets first, and then they are explained more in detail. We observed that around 80% of Recommendation system development mainly concentrated on five categories of the datasets, which includes Movie, Book, Food, Music and some products purchased or some service availed. On the other side, comparatively a small number of RS considered some miscellaneous dataset for their study. Recommending Systems can help people find interesting items with a gradual increase in consumers and goods in e-commerce Systems. Recommendation Systems play an important role when the user and item database increases. Over the time, society has developed several means of communication from word of mouth to letters written, television, and now the internet. The internet has created its form of communication, which is Social Network. Social Networking sites like Facebook, Instagram, Twitter, etc provide web-based services like bringing people across the world on the same platform, at the same time thus providing a way to let them communicate with each other. These sites employ people to people recommendations based on user characteristics.

The World Wide Web is moving from a hyperlinked document network to a linked data web. There's al-ready a massive amount of data available in publicly accessible databases. In [35],a content-based recommendation system is introduced and showed the use of the available data in the Linked Open Data datasets to construct an effective recommendation system(RS) primarily focused on the information stored on the Web Internet to recommend films to end users.

In recent years, the mobile music market is experiencing rapid growth due to an increasing variety of content made available in the mobile Web environment. Customers experience a great deal of vexation when searching for the desired music from a list of hundreds of thousands of music. To make searching more justifiable a more efficient recommendations are required that match the customer's preferences. For Music Recommendation of new or unpopular tracks, a collaborative filtering method suffers from the cold-start issue

as no adequate user data will be available. The study proposed in [114] have described a latent factor model in which Deep Convolution neural networks are used to predict latent factors from music audio which tend to make sensible recommendations. A comparative analysis is also conducted between a conventional approach using a bag-of-word representation of audio signals and Deep Convolution neural net-works, where the latter outperforms the traditional approach.

6. Challenges and Future Directions

This section discusses problems and challenges in recommendation Systems and addresses various solutions that researchers provide to deal with these problems. A recommendation engine can be a gift for the modern world whereas the same engine can be a nightmare if the people on the machine can easily manipulate it. Thus, various problems faced by Recommendation Systems are discussed below:

Cold Start Problem - This problem occurs with new users entering the Systems or adding new items to the list [115]. This real issue can undermine the quality of CF significantly. It can occur in three different scenarios: a) when a new user enters b) a new item is introduced c) a new community group is formed [116], [117]. The solution to this problem is using a hybrid approach by combining content-based and collaborative filtering techniques. You can use product descriptions and features as well as user profiles to recommend products [17] to the users [118].

Data Sparsity - The profile matrix is typically sparse due to a large number of items and the inability of users to rate the objects [119]. This sparsity allows inefficient computational learning. A solution to this problem is to use the Dimensionality Reduction technique [4] to minimize unnecessary applications and products from which we do not know much and to reduce the sparsity of the consumer

[17] https://medium.com/@rabinpoudyal1995/challenges-in-building-recommendation-Systems-719a4d3cf5b2

TABLE V. Datasets detail

Dataset Domain	Dataset Name	URL
Animation Review	Anime	https://myanimelist.net/
Book Review	Goodreads	https://www.goodreads.com/
	Book-Crossing	http://grouplens.org/datasets/book-crossing
	DBbook2014	http://2014.eswc-conferences.org/important-dates/call-RecSys.html
	Douban	https://networkrepository.com/soc-douban.php
Bussiness Review	Yelp	https://www.yoochoose.com/
	GoogleLocal	https://www.yelp.com/dataset/challenge
Food Review	Dianping-Food	https://www.dianping.com/
Geographical Map Review	OpenStreetMap	https://planet.openstreetmap.org/planet/full-history/
Interest Review	Pinterest	https://www.kaggle.com/minnieliang/rec-system
Joke Review	Jester	http://goldberg.berkeley.edu/jester-data/
Movie Review	MovieLens - 100K	https://grouplens.org/datasets/movielens/100k/
	MovieLens - 1M	https://grouplens.org/datasets/movielens/1m/
	MovieLens - 10M	https://grouplens.org/datasets/movielens/10m/
	MovieLens - 20M	https://grouplens.org/datasets/movielens/20m/
	Prize	https://www.netflixprize.com/
	FilmTrust	http://www.librec.net/datasets.html#filmtrust
	Netflix	http://www.netflixprize.com
	Flixster	http://konect.cc/networks/flixster/
	FilmTrust	http://www.librec.net/datasets.html#filmtrust
	EachMovie	https://www.cs.cmu.edu/$\sim$lebanon/IR-lab/data.html
	Douban	https://networkrepository.com/soc-douban.php
Music Review	Million Songs Dataset	http://millionsongdataset.com/
	Douban	https://networkrepository.com/soc-douban.php
	YahooMusic	https://webscope.sandbox.yahoo.com/catalog.php?datatype=r&did=1
	Last.FM	https://grouplens.org/datasets/hetrec-2011/
Product Review	YooChoose	http://2015.recsyschallenge.com/
	Amazon	https://jmcauley.ucsd.edu/data/amazon/
	Ciao	http://www.librec.net/datasets.html#ciaodvd
	treadesy	http://jmcauley.ucsd.edu/data/tradesy/
	ciao	http://www.librec.net/datasets.html#ciaodvd
	Epinions	https://snap.stanford.edu/data/soc-Epinions1.html
	ciao	http://www.librec.net/datasets.html#ciaodvd
Video Game Review	steam	https://store.steampowered.com/
Web bookmarks Review	Delicious	https://paperswithcode.com/dataset/delicious
Web pages	Wikipedia	https://en.wikipedia.org/wiki/Wikipedia:Namespace https://en.wikipedia.org/wiki/Wikipedia:Redirect

rating matrix [120], [121].

Scalability - In many places, there are millions of users and products where these Recommending Systems make recommendations [122]. Hence, evaluating recommendations often includes a considerable amount of computational power [123], [120], [124]. Therefore, Amazon uses a topic diversification algorithm incorporated with a collaborative filtering method for recommending items to its users to overcome the problem of scalability [1].

Shilling Attacks - If a malicious user or competitor joins a program and tries to give false ratings on certain products to either increase the popularity of the product or to decrease its popularity, then it corrupts the software and exploitation of users occur [120]. These attacks will undermine the trust of the Recommendation Systems and decrease the efficiency and reliability of the Recommendations. Different types of Shilling attacks are defined, such as 1. Random Attack 2. Probe Attack 3. Segment Attack 4. Bandwagon Attack 5. Average Attack in [125], [126]. An algorithm is suggested in [127] to detect and isolate shilling attackers. Various indicators have been used here to detect and classify whether or not a user is malicious by observing the rating patterns of the user. It is therefore possible to make high quality recommendations by deleting the profiles of such malicious users.

Grey Sheep Problem - This problem usually occurs in collaborative filtering RS when a strange user or a group of users enters the Systems whose preferences do not match to any category or match to multiple categories [128] and thus they may introduce difficulties in producing accurate recommendations [129]. Through introducing offline clustering strategies such as k-means clustering, it is possible to detect and differentiate grey sheep users from other normal users. It is possible to enhance the recognition of grey-sheep users by using the histogram intersection technique[130] to re-produce the user-user similarity distribution.

However, there are several ways to fix the difficulties and challenges of RS. In order to mitigate the cold start problem, the IP address of a user can be utilized. A user's IP address can provide contextual information such as location, time, etc. It is possible to recommend items based on location and time duration if they have been purchased by users with similar locations and times. Moreover, the latest and trending items must be available in the dataset of RS to show them to users. On the contrary, outdated items must have been removed at the time of recommendations to users. To achieve this, one should filters items using some cut-off date. Information overload can result in building the datasets blended with multiple domains, which consequently can cause performance degradation issues in RS. with the aim of getting rid of this problem, A recommendation system is built which itself comprises several functional components. Each component is mapped with a specific domain of the dataset. Whenever a recommendation is to be performed, the respective component is selected from the pool. One can achieve a more accurate recommendation system by practicing this strategy.

Besides, to build a recommendation system having more accuracy, deep learning methods can be practiced. It may attain the objective of dimensionality reduction in the massive dataset remarkably. It helps extract latent features of the dataset which may lead to perfect recommendations than before. With the huge number of users and items in the Recommendation System, the sparsity problem is created. The matrix of users-items finds zeros in the majority of the cells. It has been found, however, that clustering can resolve this issue to a certain extent. In addition, some natural language processing techniques can be used to solve the problem of synonyms and abbreviations.

In the response, there are remarkable research work carried out by different researchers to mitigate the above mentioned issues of RS. Figure 8 depicts the proportion of the problem targeted by the investigators using variety of techniques such as association rule mining, clustering, random decision forest, non-negative matrix factorization, a deeper graph neural network, rough set theory, genetic algorithms, etc. The cold-start problem dominates the others, because there is ever-increasing users and items in the recommendation systems. Furthermore, the development of RS variations over the years has been depicted in Figure 9. It shows that how the changes have taken place over the course of time and still they are in use.

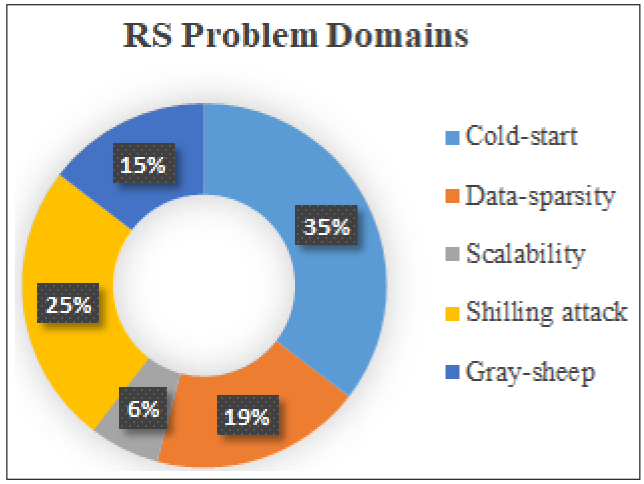

Figure 8. The problem domain alleviation

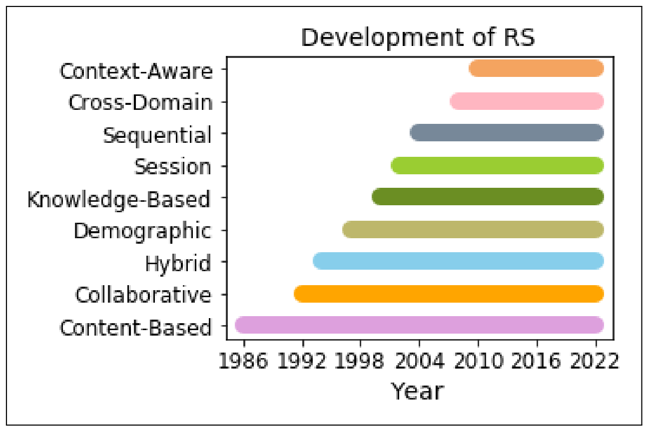

Figure 9. The development of RS

7. Conclusion

Recommendation Systems have made significant improvements over the last decade in creating numerous content-based, collaborative filtering, demographic, and various hybrid-based Systems. Such Systems are proving to be very useful in dealing with information overload on the internet and in delivering robust recommendations. In this paper, we reviewed a variety of approaches used to build Recommendation Systems and also addressed potential extensions that should provide better recommendations. To measure the effectiveness of different recommendation Systems and various approaches used to build RS, we compared works by different authors who implemented their recommendation Systems using either content-based, collaborative filtering or hybrid methods based on specific performance metrics such as MAE, RMSE, Precision, Recall, and F measurements. This comparison is depicted in the form of a table that gives a precise idea of how accurate a model is as compared to other models. On studying various recommendation Systems from different domains like Restaurant Recommendation Systems, Movie Recommendation Systems, Music Recommendation Systems, Recommendation Systems for tourism industry, a Personalized recommendation Systems and many other Recommendation Systems that have been developed, we have presented various applications of different approaches employed to develop Recommendation Systems in multiple domains. Various problems such as Cold-Start, Data Sparsity, and

Scalability are commonly faced by the Collaborative filtering approach whereas many other existing recommendation models suffer from problems like Grey Sheep and Shilling Attacks. These problems have been discussed in detail and possible solutions are suggested. Thus, future research should concentrate on improvising existing methodologies and algorithms to provide accurate recommendations to users.

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Dhruval Patel is currently pursuing a Master's degree in Computer Science at Arizona State University - Tempe, Arizona, USA. He received his B.E. degree in Computer Engineering from Gujarat Technological University - Ahmedabad, Gujarat, India. He has worked in the IT industry as Software Development Engineer, Data Engineer and Machine Learning Engineer during his internships at different organizations. He has written one research paper and one book chapter in the past, both of which were published by reputable publishers. His areas of interest in research include Big Data, Cloud Computing and Machine Learning.

Foram Patel Foram Patel was raised in the Indian state of Gujarat, where during her high school years she grew her interest in computer technology. She graduated with her Bachelor's in Computer Engineering from Vishwakarma Government Engineering College. While pursuing her undergraduate degree, she discovered her interest in research and wrote two conference papers. She is currently pursuing her master's degree in Computer Science at the University of Texas at Arlington, where she is doing her Thesis research on the topic of Mitigating misinformation spread on social media. Her main areas of interest in research are deep learning, natural language processing and fact-checking.

Uttam Chauhan has been working as an Assistant Professor in the Computer Engineering Department, Vishwakarma Government Engineering College – Ahmedabad, Gujarat, India. Prof. Uttam Chauhan has received his Ph.D. in Computer Engineering from Gujarat Technological University, Ahmedabad. He is having over 15 years of experience teaching undergraduate and postgraduate students of Computer Engineering and Information Technology. He has published more than 12 International Journal and Conference papers. He has served as a reviewer of reputed journals and conferences. He has worked as a member of the Technical Program Committee in the International conference IC4S-2019 and IC4S-2020. He has guided several M.Tech students in their dissertation work. He has been supervising three Ph.D. scholars. His research interest includes Natural Language Processing, Machine Learning, and Data Analytics.