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REVIEW OF RECOMMENDER SYSTEM: TAXONOMY AND PERFORMANCE EVALUATION

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ABSTRACT

Recommendation systems play an increasingly important role in online web services for the personalization and recommendation of content to individual users. The quantity and quality of user-based information have progressed, and present an opportunity to further tailor recommendations to users. The dynamic nature of data and the velocity at which cloud applications and mobile

INTRODUCTION

With the rapid growth of the Internet, the explosive evolution and variety of information available on the web, and the accessibility of a large number of products for sale on e-commerce sites(Darwish, Madbouly et al. 2014), social network application have led to information overload problem (Meng, Hu et al. 2013, Darwish, Madbouly et al. 2014). There is, therefore, the need for a system that will help in accessing relevant information accurately, and efficiently. One such system is Recommender System (RS).

An RS tries to predict the rating or preference of an item that the user would give. Most e-commerce website based on user's preference and testes uses RS to make a recommendation and personalize the website (Gupta and Gadge 2014). RS helps in addressing the problem of information overload by assisting a user to discover significant information that meets their need. When trying to locate relevant information at the right time, users face the problem of data sparsity and managing a vast array of information (Bobadilla, Ortega et al. 2013). RS cut across many areas of research such as data mining, e-commerce,

devices need, necessitate an efficient recommendation strategy. The recommendation system has been a subject of discussion in recent years in order to improve accuracy and prediction among others. The objective of this paper is to review the existing recommendation techniques and develop a taxonomy that will enable researchers to understand and select a technique as a basis for recommendation mechanisms. In this research five (5) recommendation approaches have been studied based on 33 articles related to the area. The characteristics of the recommender system have been studied and analyzed based on their requirements and the dataset used. Seven (7) requirements were used for the research such as accuracy of prediction, scalability, sparsity, cold start, diversity, precision, and recall. The research observes that most researches focus more on addressing the accuracy of prediction, sparsity, precision, and recall with less attention on scalability, cold start, and diversity. The research uncover some key future topics that can improve the progress and implementation of the recommender system.

machine learning, human-computer interaction, information retrieval (Ricci, Rokach et al. 2011).

RS was first presented as an independent field in the 1990s (Akhil and Joseph 2017). Since then, several researches have been carried out in this area with the sole aim of producing better recommendations. Websites like Amazon personalize their online store for each customer by showing them items suited to their interest. This results in a better customer experience, increased customer loyalty, and click-through rates resulting in increased profitability of the website. Similarly, websites related to movies, books, music, news, jokes, and restaurants can predict items its users are likely to purchase based on their previous likes and dislikes and viewing habits (Gupta and Gadge 2014).

RS can be categorized into Content-Based Filtering (CBF), Collaborative Filtering (CF), Demographic Recommendation (DR), Knowledge-Base Recommendation (KBR), and Hybrid. The CBF referred to as cognitive filtering, recommends items based on a comparison between the content of the items and a user profile. The vector space model and latent semantic indexing are two methods that use these terms to represent documents as vectors in a multi-dimensional space. While, in DR, the demographic information about the user is leveraged to learn classifiers that can map specific demographics to ratings or buying propensities (Aggarwal

2016). CF recommends to the active user the items that other users with similar tastes liked in the past. The similarity in taste of two users is calculated based on the similarity in the rating history of the users (Ricci, Rokach et al. 2011). KBR offers recommendations that already exist in databases or knowledge bases that are therefore not dynamically influenced by ratings or recent preferences.

In the past decade, there has been a vast amount of research in the field of RSs, mostly focusing on designing new algorithms for recommendations. Most researchers who suggest new recommendation algorithms compare the performance of their new algorithm to a set of existing approaches. Such evaluations are typically performed by applying some evaluation metric that provides a ranking of the candidate algorithms (usually using numeric scores) (Gunawardana and Shani 2009). The RS evaluation requirements (metrics) are timeliness, accuracy of prediction, diversity, coverage, precision, recall, F1-measure, and receiver operating characteristics. An efficient RS needs to satisfy these requirements.

There are different RS techniques available. To the knowledge of the researcher, A combination of taxonomy and performance evaluation of RS has not been fully investigated. There is no enough comparative study to help researchers understand and compare the different RS techniques. Hence the need for this research.

The main contribution of this paper is as follows:

- Presenting a systematic review and studying the existing methods in RS.
- Exploring the major issues/challenges in RSs.
- Classifying the RS algorithms.
- Provide assessment using accuracy of prediction, scalability, sparsity, cold start, diversity, precision, and recall metrics.

The remainder of the paper is organized as follows. Section 2 explains the RS techniques as explained by researchers. RS Challenges are presented in section 3. While Section 4 present the RS requirements. Related literature is presented as explained by researchers. Section 5 describe the taxonomy of RS. In Section 6, we present the discussion. Lastly in section 7, we conclude the research and future direction.

Recommender System Techniques:

RS are software tools and techniques providing suggestions for items to be of use to a user (Ricci, Rokach et al. 2011). It is mainly used in various domains like online

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booking, online shopping, audio and video recommendations, and so on (Manjula and Chilambuchelvan 2016). The good examples of RS are suggesting news articles based on reader interest, and offering products based on customer purchase history (Rajaraman and Ullman 2011). Different suggestions from recommendation systems require different information filtering techniques. RS are categorized into Knowledge-Based, Demographic, Content-Based Filtering, Collaborative Filtering, and Hybrid. This section outlines the various recommender system techniques and their challenges.

Knowledge-Based Recommendation System:

A KBRS generates recommendations based on domain knowledge. A user will get a recommendation based on his particular profile and the behavior of other users will not be taken into account at all, or when it is, it will not play a central role in determining the recommendation (Bouraga, Jureta et al. 2014). Examples include items such as real estate, automobiles, tourism requests, financial services, or expensive luxury goods (Aggarwal 2016). KBRS is broken down into case-based and constraint base KBRS. Case-based recommenders determine recommendations on the basis of similarity metrics (Ricci, Rokach et al. 2011). While in constraint-based systems users typically specify requirements or constraints (e.g., lower or upper limits) on the item attribute. Domain-specific rules are used to match the user requirements to item attributes (Aggarwal 2016).

Demographic Recommendation System (DR):

This system aims to categorize the users based on attributes and make recommendations based on demographic classes. The algorithms first need a proper market research in the specified region accompanied with a short survey to gather data for categorization. Demographic techniques form "people-to-people" correlations like collaborative ones, but use different data. The benefit of a demographic approach is that it does not require a history of user ratings like that in collaborative and content based recommender systems (Bluepi 2019).

Content-Based Recommendation System (CBR):

Content-based method provides recommendations by analyzing the description of the items that have been rated by the user and the description of items to be recommended. A profile is created for each user or item to describe its inherent

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characteristics. For instance, the attributes of a movie profile may be its genre, director, actors, its box office popularity, etc. User profile may include their selected items, ratings, demographic information, etc. The profile helps recommender systems associate users with matching items (Kumar and Sharma 2016). CBR cannot generate suitable suggestions if the content analyzed for an item does not contain appropriate information for categorization. This limitation can overcome by, feature weighting (FW) which assigns different levels of importance to different features (Son and Kim 2017).

Collaborative Filtering Recommender System (CFR):

Collaborative filtering is the most widely used and effective method of recommending items to users. CFR analyses the users' interest, finds users who are similar to target users in group of users, and synthesizes these similar users' ratings for different items, to produce the target users' recommendations. The basic assumption of CF is that: If the users had the same preferences in the past, such as they browsed or bought the same book, they will have similar preferences in the future (Li and Wang 2019). There are two categories of CFR techniques as memory-based and model-based.

1. The memory-based or neighborhood-based (Aggarwal 2016) methods act on the matrix of ratings. They use the ratings of users on items to compute similarities among different users or items in order to select neighbors and recommend their items to the current user (Bobadilla, Hernando et al. 2011). Memory-based methods usually provide a good recommendation accuracy but they suffer a high computation time that increases along with the number of users and items (Karabadji, Beldjoudi et al. 2018). This method is further divided into user-based and item-based. The user based CF assumes that a good way to find a certain user's interesting item is to find other users who have a similar interest while the item based assumes that to make the rating predictions for target item B by user A, the first step is to determine a set S of items that are most similar to target item B (Aggarwal 2016). The techniques used in memory based CFR include Pearson Correlation, Cosine Similarity.
2. Model-based methods create models to generate recommendations and focus on describing user's behaviours to predict the ratings of items. Thus, in comparison with memory-based methods, model-based methods are

faster yet provide less accurate predictions (Karabadji, Beldjoudi et al. 2018). Models are developed using different data mining, machine learning algorithms to predict users' rating of unrated items. There are many model-based CF algorithms. Bayesian networks, clustering models, latent semantic models such as singular value decomposition, probabilistic latent semantic analysis, multiple multiplicative factor, latent Dirichlet allocation and Markov decision process based models.

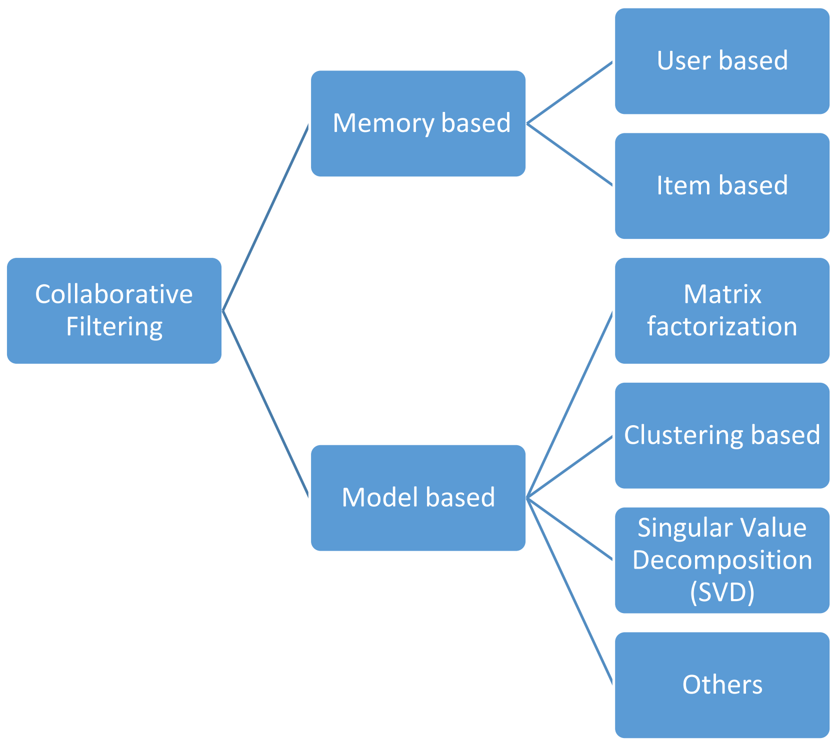

Figure 1: Collaborative Filtering Method

Hybrid Recommender System"

This system combines the above mentioned recommender system techniques. It takes the advantage of one system to overcome the weakness of the other system. For example, CF methods suffer from new-item problems, i.e., they cannot recommend items that have no ratings. This does not limit content-based approaches since the prediction for new items is based on their description (features) that are typically easily available. Given two (or more) basic RSs techniques, several ways have been proposed for combining them to create a new hybrid system (Ricci, Rokach et al. 2011). There are three (3) ways of creating Hybrid RS:

1. **Ensemble design**: Result from off-the-shelf algorithm are combined into a single or more robust output. For example, one might combine

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the rating outputs from a content-based and a collaborative recommender into a single output (Aggarwal 2016).

2. **Monolithic design**: An integrated recommendation algorithm is created by using various data types. A clear distinction may sometimes not exist between the various parts (e.g., content and collaborative) of the algorithm. In other cases, existing collaborative or content-based recommendation algorithms may need to be modified to be used within the overall approach, even when there are clear distinctions between the content-based and collaborative stages. Therefore, this approach tends to integrate the various data sources more tightly, and one cannot easily view individual components as off-the-shelf black-boxes (Aggarwal 2016).

3. **Mixed system**: The systems use multiple recommendation algorithms as black-boxes, but the items recommended by the various systems are presented together side by side (Aggarwal 2016).

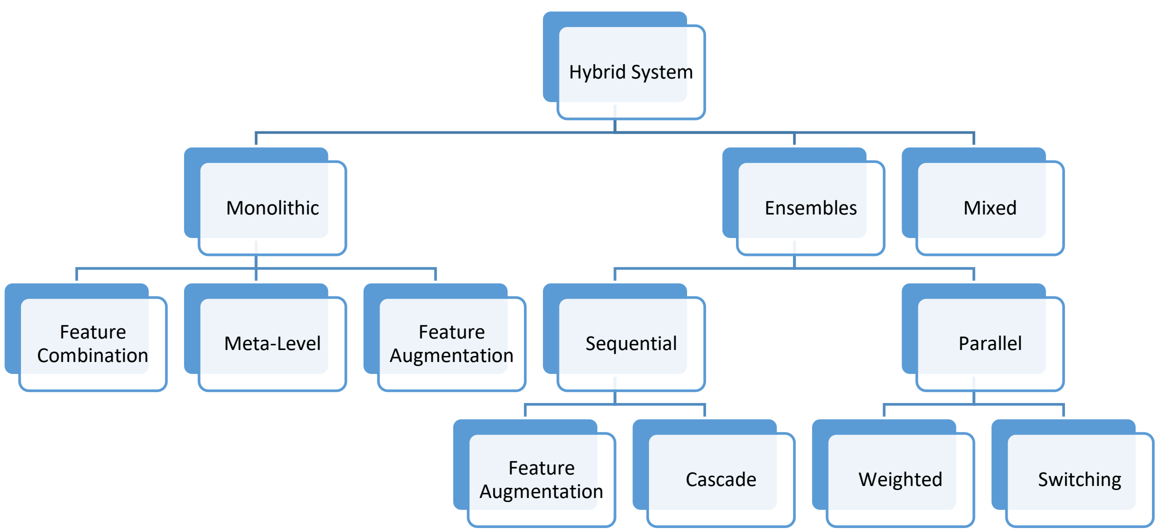

Figure 2: Hybrid Recommender System.

Recommender System Challenges:

Recommender system was introduced to provide recommendation for item to users. Most at times, the system may need to provide recommendation for item without the required details about the items/users. Several challenges are abound to recommender system. They include:

1. **New user problem:** It is also known as the lack of information problem. When the new user enter in the system, system doesn't have sufficient

information of user profile and his /her preference for particular products, so proper item profile cannot created based on that So as a result poor recommendation can be done. This problem is popular in content based recommendation.

2. **Overspecialisation:** This is another problem in recommender system in which the items similar to those rated high by the user is given as recommendations which also means that the user might have already bought or experienced the item. Hence the recommendations will not shed much interest on the user and there is a very high probability that user might leave using the system because it is not able to be of much use to the user.
3. **First Rater Problem:** The first-rater (or early-rater) problem arises when it is impossible to offer recommendations about an item that was just incorporated in the system and, therefore, has few, or even none, evaluations from users (Moreno, Segrera et al. 2011).
4. **Cold start problem:** One of the major problems in recommender systems is that the number of initially available ratings is relatively small. In such cases, it becomes more difficult to apply traditional collaborative filtering models. While content-based and knowledge-based methods are more robust than collaborative models in the presence of cold starts, such content or knowledge might not always be available (Aggarwal 2016). Cold start is commonly occurred when a new user joining the system, since there is no information about him, it would be impossible to determine his behaviour in order to provide him recommendations (Moreno, Segrera et al. 2011) or the system has not yet received enough ratings to generate quality recommendations to any users (Kotkov, Wang et al. 2016).
5. **Sparsity**: Sparsity is a problem common to most recommender systems due to the fact that users typically rate only a small proportion of the available items (Ricci, Rokach et al. 2011). It occurs mainly due to the fact that the no of items available to be rated is very high when compared to the number of items already rated by the user. So when a user item matrix is populated only a very few entries will be marked which causes the matrix to be parse leading to poor recommendations. This problem can be overcome by Singular Value Decomposition (SVD)

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to reduce dimensionality of sparse rating matrix (Akhil and Joseph 2017).

6. **Scalability**: As recommender systems are designed to help users navigate in large collections of items, one of the goals of the designers of such systems is to scale up to real data sets. As such, many algorithms are either slowed down or require additional resources such as computation power or memory (Ricci, Rokach et al. 2011). Scalability issue arises as the number of users, items and ratings information grows day by day. Even with the growing amount of information recommender systems are expected to respond quickly with recommendations for the online customers and it demands a higher scalability (Akhil and Joseph 2017). It is typically measured by experimenting with growing data sets, showing how the speed and resource consumption behave as the task scales up (Ricci, Rokach et al. 2011).
7. **Popularity bias**: It is the tendency for popular items to be recommended more frequently (Kamishima, Akaho et al. 2014).
8. **Shilling Attack:** In a recommendation system where everyone can give the ratings, people may give lots of positive ratings for their own items and negative ratings for their competitors. It is often necessary for the collaborative filtering systems to introduce precautions to discourage such kind of manipulations (Wikipedia 2018).

Recommender System Requirements:

The main requirement of any RS is to provide prediction accurately and within the shortest possible time. To rate the performance of a RS, there is the need to identify the actual characteristics of the system. Some of these characteristics came from the system ability to overcome the challenges hindering the performance of the system.

In order to rate the performance of any RS algorithms, nine (9) requirement/metrics are considered viz; accuracy of prediction, timeliness, diversity, F-Measure, precision, recall, receiver operating characteristics, error rate, coverage. These requirements are described below:

1. Accuracy of prediction: It is used to compare the recommendation algorithms. It is necessary to use the same dataset for different algorithms.

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Prediction accuracy is mainly concerned with predicting users' rating. This metric often has guiding significance to the overall performance of RS (Chen and Liu 2017). It uses three metrics Mean Absolute Error, Mean Square Error and Root Mean Square Error.

2. Timeliness: Measure the extent to which the items are new or long listed in the market. It is also referred to as a quantity measuring whether an item is still relevant in current time. A low timeliness value indicates that the item is already out-of-date(Zhang, Liu et al. 2017).
3. Coverage: The coverage with respect to a user is the fraction of the total item domain which algorithm could possibly recommend to the user (Ekstrand, Riedl et al. 2011). It also refers to the proportion of items recommended to total items. A good RS does not require good precision but also high coverage (Chen and Liu 2017).
4. Diversity: Diversity generally applies to a set of items, and is related to how different the items are with respect to each other. It can also be regarded as dissimilarity of recommended items. Diversity in a list of items can be measured, in terms of the objective variety of items in the list (e.g. as pairwise dissimilarity). A good RS should satisfy different user requirements (Castells, Vargas et al. 2011).
5. Precision: It is one of the most popular metric in RS. Precision measure describes what proportion of recommendations was actually suitable for the user. It also describes what proportion of the suggested pairings for a user result in matches. The false positive rate describes what proportions of unsuitable candidates are paired with the active user. (Gunawardana and Shani 2009).
6. Recall: Describes the proportion of the user favourite items that are not missed (Chen and Liu 2017). It can also be said that recall measures is the portion of relevant items that have been retrieved (Nilashi, Ibrahim et al. 2018).
7. F-Measure: The F-measure or F-Score is a measure of a statistic test's accuracy. It considers both precision and recall measures of the test to compute the score. We could interpret it as a weighted average of the precision and recall, where the best F1 score has its value at 1 and worst score at the value 0 from (Caraciolo 2011).
8. Receiver Operating Characteristics (ROC): ROC emphasizes the proportion of items that are not preferred that end up being recommended (Gunawardana and Shani 2009).
9. Error Rate: It measures the total number of incorrect predictions against the
total number of predictions (Mahboob and FATIMA 2015).

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Related Literature:

Many researches have been carried out to survey the different techniques in recommender system. Most of the research either centres on a particular recommender system techniques or surveys it looking at the particular angle. For instance, (Gunawardana and Shani 2009) work on the proper construction of offline experiments for deciding on the most appropriate algorithm. They further discuss the well-known metrics and demonstrated that using improper evaluation metrics can lead the selection of improper algorithm. (Ekstrand, Riedl et al. 2011), discuss a variety of choice, issues and the best practiced to the research in the area of recommender system.

(Akhil and Joseph 2017), in their paper, focuses on reviewing progress made in only three basic RS such as collaborative filtering, content based filtering and hybrid. They were able to list some challenges faced by those RS. Their work does not cover categorising RS and measuring their performance. (Beel 2017), Consider measuring metric as time series which will enable researchers view the behaviour of RS in the future and draw conclusion about the algorithm.

(Kunaver and Požrl 2017), Looked at the state of the art survey on diversity as a metric and provide insight into the research in this area. (Mahboob and FATIMA 2015), surveyed a graphical model based, supervised, semi-supervised and unsupervised algorithms. Their research centres on those four categories mentioned above. (Bellogin, Castells et al. 2011), Compared five evaluation methodologies on three state of the art recommenders under two evaluation conditions. Their work does not look at the different categories of RS.

(Sielis, Tzanavari et al. 2015), reviewed the different types of RS, techniques and methods used for building such system, the algorithms used. They categorised the metrics into prediction based metrics, information retrieval related metrics and diversity, novelty and coverage. Their research does not review any research paper in order to evaluate the algorithms. (Chen and Liu 2017), their research discusses three (3) classical methods – offline analytics, user study and online experiment – to evaluate the performance of recommender system. They also reviewed some performance evaluation metrics from only four perspectives – information retrieval, machine learning, human-computer interaction and software engineering. Their research does not review any RS algorithms and provide categorisation. (Shah, Gaudani et al. 2016), their research covers the three well-known recommender systems – collaborative filtering, content based and

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hybrid system. They only review the techniques, algorithms and challenges. The do not provide any state of the art categorisation of the techniques and evaluation.

Dataset used in RS:

Performing real-time execution of RS is very complex considering the unexpected nature of the environment and the evaluators. Most researchers perform their experiment in a simulated environment in order to provide the necessary accuracy, and precision. The performance of RS also relies on the amount of training data. Previous studies tend to use transaction records (users' actual purchase decisions) from online e-commerce Web sites as supervised information. However, such data are not always available as e-commerce companies could choose not to reveal their transaction data. ***Table 1*** describes the dataset used for the papers used in this research.

The dataset mostly used are from some reputable companies that have customers who rate their products. One such company is the GroupLens who provide MovieLens dataset in different sizes, such as 100K containing 100,000 ratings, 1M and the 20M. Other companies are the Yahoo! Which provide rating for both music and movies. The Netflix provide movie ratings while the Book Crossing Contain ratings for document.

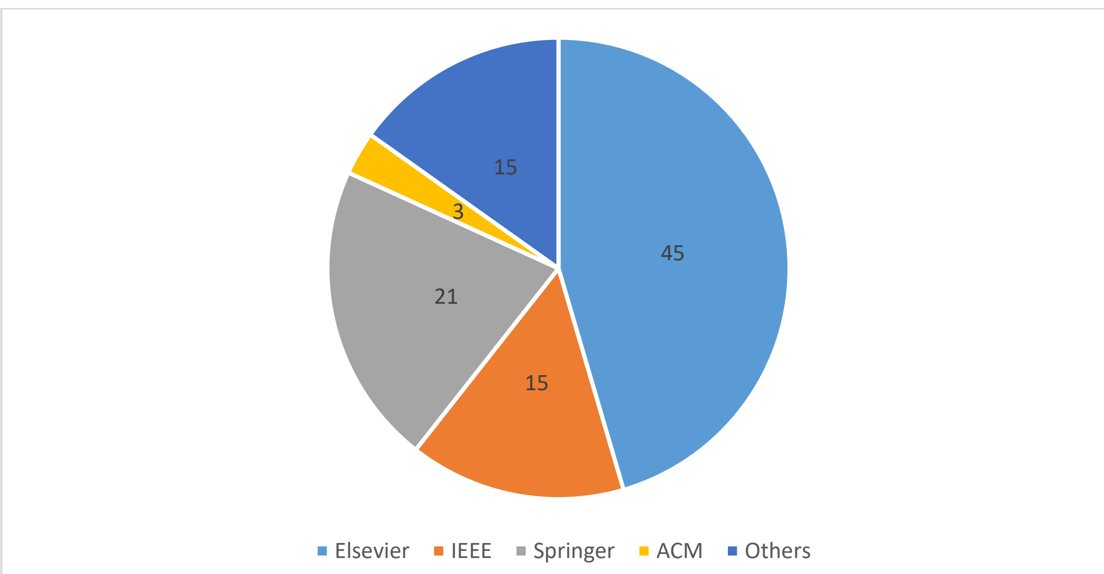

Figure 3: Distribution of Research Papers Used for This Research by Web Jounal

Adopted Categorisation of Recommender System

This research paper was conducted using 4 different RS techniques from 50 different articles which are related to RS. Out of the 50 papers, 33 were selected for the categorisation, review and analysis. These articles were selected from reputable and cited resources and publication with their impact factor such as Springer, Elsevier, IEEE, etc. 45% of the papers were from Elsevier, 15% from IEEE, 21% from Springer, 3% from ACM and 15% from other Science Journals *(see Figure 3)*. The first review carried was to collect all the dataset used in each of the research paper ***(Table 1)***, while the 2nd was the detail review of the papers. Table 2 outline the papers used in this research employed and the detail review which included the methodology used, problem of the methodology and the solution to the problem.

This research paper outline several challenges hindering RS performance which in the end will help researchers in these areas for possible solution and also provide further improvement in the field.

Several RS requirements were outlined in section 4.0. Out of the 9 outlined, 4 were picked for the review and combined with the RS challenges. These requirements included – accuracy of prediction, scalability, sparsity, cold start, diversity, precision, recall.

Table 1: Dataset Used for Recommender System

S/N	RS Technique	Author(s)	Title	Size of Dataset	Description
1.	Knowledge Base	(Maalej, Mtibaa et al. 2017)	Context Similarity Measure for Knowledge-Based Recommendation System	N/A	The evaluation is done using known measures.
2.	Demographic	(Wang, Chan et al. 2012)	Applicability of Demographic Recommender System to Tourist Attractions: A Case Study on TripAdvisor	Total Dataset 33,040	Tourist were selected from Six cities dataset which included: New York City 6,360 Paris 6,890 London 11,800 Chicago 2,640 Rome 2,100 Berlin 3,250
3.	Demographic	(Al-Shamri 2016)	User Profiling Approaches for Demographic Recommender Systems	MovieLens 100K (100,000)	The dataset contain 100,000 ratings from 943 users on 1,820 movies.

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4.	Demographic	(Zhao, Li et al. 2016)	Exploring demographic information in social media for product recommendation	Total qd pairs is 1103 and number of instances is 29168	The dataset is on 3 products; phone, camera and laptop with qd pairs of 170, 496 and 437 and instances 4732, 12741 and 11795 respectively.
5.	Demographic	(Moreau, Pivert et al. 2017)	A Typicality-Based Recommendation Approach Leveraging Demographic Data	MovieLens 1M (1,000,209)	The MovieLens dataset contain 3,883 movies partially rated by 6,040 users. It is split into training and test as 80% and 20% respectively.
6.	Content-Based	(Wita, Bubphachuen et al. 2017)	Content-based Filtering Recommendation in Abstract Search using Neo4j	Abstract page of student report of between 300 – 350 words.	The dataset were text document of student retrieved from Chiang Mai University
7.	Content-Based	(Son and Kim 2017)	Content-based filtering for recommendation systems using multiattribute networks	MovieLens 1M (1,000,029 ratings)	The ratings was provided by 6040 users for 3952 movies.
8.	Content-Based	(Shu, Shen et al. 2018)	A content-based recommendation algorithm for learning resources	Book Crossing dataset of 10393 books, 26387 users and 407573 ratings score, 10393 book introductions.	The sample dataset is taking from book crossing database in 2004
9.	CF (Memory-Based)	(Liu, Hu et al. 2014)	A new user similarity model to improve the accuracy of collaborative filtering	Movielens (100K and 1M) ratings Epinions 664,824 reviews	Movielens: 100K contains 100,000 ratings with 943 persons and 1682 movies. 1M, it includes 6040 users and 3952 movies with 1,000,209 ratings. Epinions: 49,289 users who have rated a total of

					139,738 different items at least once. There are 40,163 users who have rated at least one item. The total number of reviews is 664,824.
10.	CF (Memory-Based)	(Levinas 2014)	An Analysis of Memory Based Collaborative Filtering Recommender Systems with Improvement Proposals	Movielens 100K	Contain 100,000 ratings from a pool of 943 users, voicing preferences on 1682 movies.
11.	CF (Memory-Based)	(You, Li et al. 2015)	An Improved Collaborative Filtering Recommendation Algorithm Combining Item Clustering and Slope One Scheme	MovieLen 1M dataset containing 1,000,209 ratings	The dataset rating was from 6,040 users on 3,900 movies. The rating value ranges from 1 – 5 with sparsity of 0.958.
12.	CF (Memory-Based)	(Xiaojun 2017)	An improved clustering-based collaborative filtering recommendation algorithm	MovieLens dataset 21,622,187 ratings	The dataset was from 234,934 users on movie ranging from 1995 – 2015 and 516,139 tags of 30,106 movies
13.	CF (Memory-Based)	(Al-Bashiri, Abdulgabber et al. 2018)	An improved memory-based collaborative filtering method based on the TOPSIS technique	Movielens 100K and 1M	100K Contain 100,000 ratings from a pool of 943 users on 1682 movies. 1M contain contains 1,000,209 ratings of approximately 3,900 movies from 6,040 users
14.	CF (Memory-Based)	(Karabadji, Beldjoudi et al. 2018)	Improving Memory-Based User Collaborative Filtering	Grouplens – MovieLens 100K and 1M	The 100K dataset includes 100000 ratings by 943 users 1682 movies,

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			with Evolutionary Multi-Objective Optimization		while 1M dataset ratings from 6000 users on 4000 movies
15.	CF (Memory-Based)	(Alshammari, Kapetanakis et al. 2018)	A Triangle Multi-Level Item-Based Collaborative Filtering Method That Improves Recommendations	Three dataset used: ● MovieLens 100K containing 100,000 ratings. ● MovieLens 1M containing 1,000,209 ratings. ● Yahoo Movies containing 211,111 ratings	● The ratings are from Sept 1996 – Apr 1998 with 943 users and 1,682 movies. Each user rated at least 20 movies. ● The 1M ratings were made from 3,900 movies by 6,040 users. Ratings was made by users ● The Yahoo movie ratings was made by 7,642 users on 11,915 movies The dataset were evaluated using cross validation with 5 folds and number of neighbors of 3, 10, 30, 50, and 100
16.	CF (Memory-Based)	(Wang, Yih et al. 2020)	Improving Neighbor-Based Collaborative Filtering by Using a Hybrid Similarity Measurement	Movielens 100K and 1M datasets were used.	The MovieLens 1M dataset contain 1,000,209 ratings and was rated by 6,040 users on 3,706 movies. While the 100K dataset contain 100,000 ratings from a pool of 943 users on 1682 movies.

17.	CF (Memory-Based)	(Vranić, Milošević et al. 2020)	A Recommender System with IBA Similarity Measure	Datasets used: • Movielens 100K • Movielens 1M • CiaODVD	100K and 1M datasets see above. CiaoDVD contains 35835 ratings given by 2248 users over 16861 movies.
18.	CF (Model-Based)	(Ortega, Hernando et al. 2016)	Recommending items to group of users using Matrix Factorization based Collaborative Filtering	Uses both MovieLens 1,000,209 and Netflix 100,480,507	The MovieLens of 1000209 ratings was made by 6,040 users from 3,706 movies in 2000. The Netflix 100480507 ratings on 17770 movies by 480189.
19.	CF (Model-Based)	(Shi, Luo et al. 2017)	Long-term Performance of Collaborative Filtering Based Recommenders in Temporally Evolving Systems	Two dataset were used: • MovieLens 1,000,209 ratings. • Netflix 93,945 ratings.	The MovieLens dataset was rated by 6,040 users on 3,706 movies. While the Netflix was rated by 2,000 users on 4,088 movies.
20.	CF (Model-Based)	(Du, Yao et al. 2017)	A new item-based deep network structure using a restricted Boltzmann machine for collaborative filtering	Two data set used: • 1M MovieLens dataset • 100K MovieLens dataset	
21.	CF (Model-Based)	(Duma and Twala 2018)	Optimising Latent features Using Artificial Immune System in Collaborative Filtering for Recommender Systems	Movielens 100K Book-crossing of 1,149,780 book ratings	1,149,780 book ratings (ranging from 1 to 10) from 278 858 users for 271 379
22.	CF (Model-Based)	(Li and Wang 2019)	A new recommendation algorithm combined with spectral clustering and transfer learning	Four classical dataset were used: • Epinions contains 664,824 ratings. • MovieLens 100K contain 100,000 ratings.	• Epnions dataset was rated by 49,290 users, 139,783 items, and 487,181

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				• MovieLens 1M contain 1 million ratings. • MovieLens+ contain 855,598 ratings	friendship data. • The MovieLens 100K were captured from 1000 users on 1700 movies. • MovieLens 1M were rated by 6,000 users on 4000 moovies. • MovieLens+ were rated by 2,113 users on 10,197 movies.
23.	CF (Model-Based)	(Ma, Guo et al. 2019)	SOM Clustering Collaborative Filtering Algorithm Based on Singular Value Decomposition	Movielens 100K dataset	The dataset contains 100,000 ratings from a pool of 943 users on 1682 movies.
24.	CF (Model-Based)	(Alhijawi, Al-Naymat et al. 2021)	Novel predictive model to improve the accuracy of collaborative fltering recommender systems	Movielens 100k and Movielens Last datasets were used.	• 100k consist of 100,000 ratings, 943 users and 1,682 moview. • Movielens Last 100,836 ratings, 610 users and 9724 movies.
25.	Hybrid	(Zhang, Tang et al. 2014)	Addressing Cold Start in Recommender Systems: A Semi-supervised Co-training Algorithm	Movielens 100K and 1M.	The dataset contains 100,000 ratings from a pool of 943 users on 1682 movies.
26.	Hybrid	(Gupta and Gadge 2014)	A Framework for a Recommendation System Based On Collaborative Filtering and Demographics	MovieLens dataset of 100K consisting of 943 users on 1680 movies.	

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27.	Hybrid	(Palomares, Browne et al. 2015)	A Collaborative Filtering Recommender System Model using Ordered Weighted Averaging (OWA) and Uninorm Aggregation Operators	N/A	N/A
28.	Hybrid	(Kumar and Fan 2015)	Hybrid User-Item Based Collaborative Filtering	MovieLens dataset of 100K were used.	The dataset consist of 1000 users on 1680 movies with each user rated at least 20 movies.
29.	Hybrid	(Panigrahi, Lenka et al. 2016)	A Hybrid Distributed Collaborative Filtering Recommender Engine Using Apache Spark	• MovieLens dataset 20M consisting 20 million ratings. • To check scalability, 1M dataset containing 1 million ratings and 10M containing 10 million ratings.	The range of ratings is 1 – 5. After preprocessing, the data set was reduced to 110615, 16409 and 441252 for users, movies and tags respectively.
30.	Hybrid	(Callvik and Liu 2017)	Using Demographic Information to Reduce the New User Problem in Recommender Systems	100K MovieLens dataset were used	The ratings were made by 943 users with minimum ratings of 20 per user.
31.	Hybrid	(Tarus, Niu et al. 2017)	A hybrid knowledge-based recommender system for e-learning based on ontology and sequential pattern mining	240 learning resources were captured containing 4000 ratings.	The dataset was divided into 2 as training and test set of 70% and 30% respectively.
32.	Hybrid	(Bagherifard, Rahmani et al. 2017)	Performance Improvement for Recommender Systems Using Ontology	Two datasets were used: • Movielens 1M dataset. • Yahoo! Webscope R4 dataset.	• The 1M dataset contain 1,000,209 ratings, 6040 users and 3952 movies.

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					• Yahoo! Dataset is divided into 2; the train set and test set.
33.	Hybrid	(Kermany and Alizadeh 2017)	A hybrid multi-criteria recommender system using ontology and neuro-fuzzy techniques	Yahoo! Movies Multi-criteria dataset.	•
34.	Hybrid	(Nilashi, Ibrahim et al. 2018)	A recommender system based on collaborative filtering using ontology and dimensionality reduction techniques	Two dataset were used: • MovieLens has 1,000,209 ratings. • Yahoo! Webscope R4 has 211,231 ratings	• MovieLens has 6,040 users on 3,952 movies with each user rating at least 20 ratings. • Yahoo ratings was made by 7,642 users pm 11,915 movies.
35.	Hybrid	(Kilani, Otoom et al. 2018)	A Genetic Algorithms-Based Hybrid Recommender System of Matrix Factorization and Neighborhood-Based Techniques	MovieLens containing 100,000 ratings. FilmTrust has 35,497 rating. CiaoDVD has 72,655 ratings.	The MovieLens ratings were from 943 users on 1,682 movies. The FilmTrust were from1,508 users and 2,078 items. CiaoDVD has 17,615 users and 16,121 items.
36.	Hybrid	(Tewari and Barman 2018)	Sequencing of items in personalized recommendations using multiple recommendation techniques	The experimental dataset are 3600 ratings of 1200 books and movies	The ratings were done 610 users and 1612 reviews.
37.	Hybrid	(Palomares, Browne et al. 2018)	Multi-View Fuzzy Information Fusion in Collaborative Filtering Recommender Systems: Application to the	• MovieLens dataset 100K • Harmonise Platform database consists 3.5K	

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			Urban Resilience Domain	users which were distributed into 3 types	
38.	Hybrid	(Chen, Hua et al. 2018)	A Hybrid Recommender System for Gaussian Mixture Model and Enhanced Social Matrix Factorization Technology Based on Multiple Interests	Two datasets were used: ● Epinions dataset. ● Tencent dataset.	● Epinions contain 1,261,218 ratings, 12,630 users, and 3,620 items ● Tencent contain 326,560 ratings, 9,650 users, and 1,650 items.
39.	Hybrid	(Da Costa, Manzato et al. 2019)	Boosting collaborative filtering with an ensemble of co-trained recommenders	Eight (8) dataset were used: ● Yahoo Movies contain 169,767 ratings. ● FilmTrust contain 35,497 ratings. ● CiaoDVD contain 280,391 ratings. ● MovieLens 2K contain 800,000 ratings. ● Jester has 1,810,455 ratings ● Book Crossing contain 1,149,780 ratings. ● Amazon Digital Music contain 206,282 ratings. ● Yahoo Music contain 196,150 ratings	● Yahoo Movies has 4,385 users with 4339 movies. ● FilmTrust has 1,508 users on 2,071 movies. ● CiaoDVD were rated by 7,375 users on 99,746 items. ● MovieLens 2K has tags of 10,000 applies to 2,113 users on 10,197 movies. ● Jester ratings was done by 23,500 users on 100 jokes normalised to 360,917 ratings made by 5,000 users on 100 items.

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					• Book crossing ratings was done by 278,858 users on 271,379 books. Sample used are 102,963 interactions by 6,628 users on 7,164 books. • Amazon music has 16,396 users on 101,708 music albums. The sample used are 59793 ratings, 6,337 users on 4,744 items. • Yahoo music ratings was made by 15,400 users on 1000 songs.
40.	Hybrid	(Yan and Tang 2019)	Collaborative Filtering Based on Gaussian Mixture Model and Improved Jaccard Similarity	Three dataset were used: • Movielens 100K • Movielens 1M • Yahoo! Webscope R4	•
41.	Hybrid	(Natarajan, Vairavasundaram et al. 2020)	Resolving Data Sparsity and Cold Start Problem in Collaborative Filtering Recommender System Using Linked Open Data	Two datasets used: • Movielens 20M containing 20 million rating, 27,000 movies and 138,000 users. • Netflix-20M containing 24,053,764 ratings, 4,499	• The Movielens-20M and Netflix-20M datasets both have sparsity of 99.4% and 98.86% respectively.

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				movies and 470,758 users.	
42.	Hybrid	(Ghasemi and Momtazi 2021)	Neural text similarity of user reviews for improving collaborative filtering recommender systems	Amazon ratings and reviews (2013). • Cell phone & Accessories • Tools & Home Improvement	The dataset consist of: • Cellphone contain 2261045 users, 319678 items, 3447249 ratings and 194439 reviews. • Tools & Homes contain 1212468 users, 260659 items, 1926047 ratings and 134476 reviews.

Table 2: List of Papers Used for this Research and their RS Technique

S/N	RS Technique	Author(s)	Title	Objectives	Solution Obtained	Problem Identified
1.	Knowledge Based	(Maalej, Mtibaa et al. 2017)	Context Similarity Measure for Knowledge-Based Recommendation System	Uses ontology to measure the similarity between the user context and other users' contexts. They integrate this measure in recommendation model to infer recommendation items based on Semantic Web Rule Language (SWRL).	Measure similarity between user context and other users'	Uses ontology to measure the similarity between the user context and other users' contexts. They integrate this measure in recommendation model to infer recommendation items based on Semantic Web Rule Language (SWRL).
2.	Demographic	(Wang, Chan et al. 2012)	Applicability of Demographic Recommender System to Tourist Attractions: A Case	Examine the integration of different machine learning methods with the system, aiming at determining	Produce tourist ratings on attraction.	Accuracy of the recommendation is low using demographic information alone.

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			Study on TripAdvisor	whether these approaches and demographic information alone are useful and effective to make prediction of the ratings.		
3.	Demographic	(Al-Shamri 2016)	User Profiling Approaches for Demographic Recommender Systems	Uses a cascaded profiling approach for the neighborhood set generation. The research also propose a single-attribute profiling approach by treating each attribute as an isolated profile and then merge their predictions	Produce recommendation using user profiling approach.	The paper uses only three (3) demographic attributes which is insufficient. Some of the approaches does not produce better result.
4.	Demographic	(Zhao, Li et al. 2016)	Exploring demographic information in social media for product recommendation	Leverage the demographic information of both products and users extracted from social media for product recommendation. An ensemble method based on the gradient-boosting regression trees was employed. They developed a bagging method to wrap around multiple additive regression trees (MART), denoted as B-MART, which can effectively reduce the variance and meanwhile improve	Uses B-MART to produce accurate product recommendation	The research has the following weaknesses: ● It is difficult to work on the product types that do not receive considerable attention on online social media. ● They only consider the explicitly set attributes on microblogs.

				recommendation accuracy.		
5.	Demographic	(Moreau, Pivert et al. 2017)	A Typicality-Based Recommendation Approach Leveraging Demographic Data	Consider two visions to typicality-based collaborative filtering applied to demographic data. They view demographics as statistical characteristics of human populations.	Produce better prediction than other state of the art methods.	Not all the result are satisfactory.
6.	Content-Based	(Wita, Bubphachuen et al. 2017)	Content-based Filtering Recommendation in Abstract Search using Neo4j	They modelled document content into graph. Document-Keyword graph was created to represent the relationship between document and its features. The data were stored as a connected graph in Neo4j graph database.	Create a Document-Keyword graph which represent relationship between document and its features.	• There is no feedback to the system. • Cannot analyse semantic relationship of the documents
7.	Content-Based	(Son and Kim 2017)	Content-based filtering for recommendation systems using Multiattribute Networks	A type of CBF that uses a multiattribute network (MN), which comprises entire attribute information for different items based on network analysis in order to improve accuracy and robustness.	• Accurately measure the similarities between directly and indirectly linked items. • Recommend variety of items to users. • Address the problem of sparsity and overspecialisation	Only eight features are used for the research which is insufficient to capture most of the hidden features of the items.
8.	Content-Based	(Shu, Shen et al. 2018)	A content-based recommendation algorithm for learning resources	Deep Learning model was employed to produce a Content-based	Produce a Content-based recommendation that recommend new and unpolular items and	• Cannot be employed in e-learning and intelligent tutoring system.

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				recommendation algorithm based on Convolutional Neural Network (CNN). CNN is constructed to make personalized recommendations and achieved a superior result.	also achieved a superior result.	• It has not been tested in news recommendation.
9.	CF (Memory Based)	(Liu, Hu et al. 2014)	A new user similarity model to improve the accuracy of collaborative filtering	Create a new improved heuristic similarity measures which is composed of 3 factors; Proximity, Impact and Popularity (PIP).	New Similarity Measures that improved similarity computation.	The value was tested using highest k-neighbors of 100 which shows decreasing value in both precision and recall.
10.	CF (Memory-Based)	(Levinas 2014)	An Analysis of Memory Based Collaborative Filtering Recommender Systems with Improvement Proposals	The paper uses four strategies to improve the performance of memory based such as Average Item Voting strategy (AIV), Indirect Estimation algorithm (IEA), Class Type Grouping (CTG) strategy and Weighted Ensemble (WE). They use Apache Mahout Collaborative Filtering Recommender System for the research.	All the proposed algorithms tested performed better than the baseline algorithms. The approach provide better way in which memory based can compete with model based approach.	• The effect of the neighbourhood size was not tested on the AIV. • The effect of changing preferences on the offline data computed was not studied. • The class type grouping algorithm did not perform better there is need for improvement. • The WE has not been tested with wide range of parameters. • The effect of coverage on accuracy has not been investigated
11.	CF (Memory-Based)	(You, Li et al. 2015)	An Improved Collaborative	They proposed a recommendation	Improve quality of collaborative filtering	DBSCAN does not work well when dealing with

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			Filtering Recommendation Algorithm Combining Item Clustering and Slope One Scheme	algorithm combining item clustering method and weighted slope one scheme. In their algorithm, they used item clustering algorithm to partition items to several clusters and apply weighted slope one scheme.	recommendation system.	data of varying densities or high dimensional data.
12.	CF(Memory Based)	(Xiaojun 2017)	An improved clustering-based collaborative filtering recommendation algorithm	The research creates a clustering-based collaborative filtering recommendation algorithm. In the algorithm, a time decay function is used to pre-process the user's rating. It then uses the project attribute vectors to characterize the projects, user interest vectors to users and also clustering algorithm to cluster the users/projects. The user's nearest neighbour is formed by using the improved similarity measure.	Produce recommendation that solve the problems of data sparsity and new users/project. It can also depict users in multi-dimension and reflect user's changing interest.	The clustering algorithm used has some weaknesses as difficulty in predicting number of clusters, initial seed have strong impact on the final result and convergence to global optima.
13.	CF (Memory Based)	(Al-Bashiri, Abdulgabber et al. 2018)	An improved memory-based collaborative	Improve the accuracy of memory based CF using Technique for Order of	Produce an alternative prediction score method called TOPSIS. Improve accuracy of recommendation.	Does not locate sets of neighbours that will produce better result.

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			filtering method based on the TOPSIS technique	Preference by Similarity to Ideal Solution.		
14.	CF (Memory Based)	(Karabadji, Beldjoudi et al. 2018)	Improving Memory-Based User Collaborative Filtering with Evolutionary Multi-Objective Optimization	They proposed a new genetic algorithm (GA) to pull up an optimized subset of profiles that improves the construction of a memory-based collaborative filtering-based recommender system.	Produce accurate and diverse recommendation.	It works on a subset of profile and ignore other profile. Those profile ignored may contain some useful information.
15.	CF (Memory-Based)	(Alshammari, Kapetanakis et al. 2018)	A Triangle Multi-Level Item-Based Collaborative Filtering Method That Improves Recommendation s	They proposed an item- based collaborative filtering (IBCF) approach with triangle similarity measures that take into account the length and angle of rating vectors between users and allow a positive and negative adjustments using a multi-level recommendation approach.	Improved prediction accuracy.	They used instance based recommendation a technique that is good for short-term.
16.	CF (Memory Based)	(Wang, Yih et al. 2020)	Improving Neighbor-Based Collaborative Filtering by Using a Hybrid Similarity Measurement	The research combined structural and rating based similarity measures. It uses Adjusted cosine for the similarity measurement on the rating based. They uses Movielens 100K, 1M	They achieve better prediction accuracy result in terms of lower MAE memory.	• The result takes time to computer. • Does not take into account the dynamic model of user preference.

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				and Netflix datasets.		
17.	CF (Memory Based)	(Vranić, Milošević et al. 2020)	A Recommender System with IBA Similarity Measure	The research uses interpolative Boolean algebra to calculate similarity among users and called it IBA similarity. Uses Movielens 100K, 1M and CiaoDVD datasets	Achieve better accuracy in terms of MAE, recall, precision and F1-measure.	● Lower result when using simple averaging ● Does not incorporate context into the recommendation system
18.	CF (Model-Based	(Ortega, Hernando et al. 2016)	Recommending items to group of users using Matrix Factorization based Collaborative Filtering	They proposed group recommendations using Matrix Factorization (MF) based Collaborative Filtering (CF). They proposed three original approaches to map the group of users to the latent factor space and compare the proposed methods in three different scenarios: when the group size is small, medium and large.	Produce group recommendation system and test using small, medium and large dataset.	Computation of the weighted does not include social structure of the group of users in which some users have more influence than others..
19.	CF (Model Based)	(Shi, Luo et al. 2017)	Long-term Performance of Collaborative Filtering Based Recommenders in Temporally Evolving Systems	The paper describes an online commercial system using bipartite network. They proposed a recommendation-based on evolution method in order to capture the temporal dynamics between	● Evaluate the performance of temporally evolving network. ● Optimization based CF has high prediction accuracy while entity relationship model has high recommendation diversity and system health.	This approach is an evaluation system. The system has not been tested using a real life system in order to see different users behaviour.

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				recommender system and users' behaviours in the temporally evolving system. The user-based CF (UCF), item-based CF (ICF) and latent factor-based model (LFM), are evaluated on the generated temporally evolving networks.		
20.	CF (Model Based)	(Du, Yao et al. 2017)	A new item-based deep network structure using a restricted Boltzmann machine for collaborative filtering	An Item-based restricted Boltzmann machine (RBM) approach for CF which use multi-layer RBM network structure to alleviate sparsity. While Batch Gradient Descent Algorithm with Minibatch to improve convergence speed.	Overcome sparsity problem and improve convergence speed.	The approach uses only one biases in the RBM model.
21.	CF (Model-Based)	(Duma and Twala 2018)	Optimising Latent features Using Artificial Immune System in Collaborative Filtering for Recommender Systems	This paper proposes an Artificial Immune System to Matrix Factorisation (AISMF) to optimize latent features as an alternative learning method for the collaborative filtering. They also come up with AISMF ensemble	Improved performance of learning method of CF. The AISMF algorithm perform better for small to medium sized matrices and also converge faster to local minima compare to SGD. While the AISMF ensemble is suitable for large matrices and converge faster to local optima	AISMF is not well suited for problem with high precision and the speed of convergence is slow and dependent on the quality of initial value as the size of matrix increase.

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				which perform better for large data set.		
22.	CF (Model Based)	(Li and Wang 2019)	A new recommendation algorithm combined with spectral clustering and transfer learning	A collaborative filtering recommendation algorithm combined with spectral clustering and transfer learning (RASCTL). First RASCTL uses spectral clustering to cluster the dimensions of users and item and then decomposes rating matrix. Finally, it make rating forecasting, share group rating and transfer learning.	Solve the problem of data sparsity and transfer knowledge between multiple rating matrix.	Only K-mean algorithm is used which has the following weaknesses: ● Difficulty in predicting number of clusters, ● Initial seed have strong impact on the final result and ● Converge to global optima.
23.	CF (Model Based)	(Ma, Guo et al. 2019)	SOM Clustering Collaborative Filtering Algorithm Based on Singular Value Decomposition	Collaborative filtering recommendation that uses SVD to low dimensional space which help in improving sparsity and then Self Organising Map (SOM) is applied to cluster the data which will help in improving scalability by partitioning the matrix.	Improve sparsity and scalability.	● SOM algorithms requires necessary and sufficient data in order to develop meaningful clusters. ● The SVD algorithm works in an offline mode. Where new user is added, cannot be handles by this algorithm.
24.	CF (Model-Based)	(Alhijawi, Al-Naymat et al. 2021)	Novel predictive model to improve the accuracy of collaborative fltering	Develop a prediction mechanism called Inheritance-based prediction which consist of	Alleviate cold start and sparsity issue of recommendation.	

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			recommender systems	adaptable predictive model and heuristic search algorithm that is applied to collaborative filtering.		
25.	Hybrid	(Zhang, Tang et al. 2014)	Addressing Cold Start in Recommender Systems: A Semi-supervised Co-training Algorithm	Propose a context-aware semi-supervised co-training method named CSEL. The Semi-Supervised Ensemble Learning Algorithm construct different prediction model and use Co-Training to allow each weak prediction to learn from it.	Solve the problem of cold start in recommender system.	The framework accommodates only one regressor from among regressors. The problem of choosing the right regressors is one of the weakness of this approach.
26.	Hybrid	(Gupta and Gadge 2014)	A Framework for a Recommendation System Based On Collaborative Filtering and Demographics	In the proposed hybrid framework, prediction using item based collaborative filtering is combined with prediction using demographics based user clusters in an adaptive weighted scheme.	Addresses user cold start problem and scalability.	• The use of K-means has some weakness such as initial seed, choosing the best value of K, etc. • The prediction may not be accurate as only demographic information and item-based were considered. • The data set used is small.
27.	Hybrid	(Palomares, Browne et al. 2015)	A Collaborative Filtering Recommender System Model using Ordered Weighted	The paper created a CF Model that calculate users' similarities degree using two aggregation	Compute Similarity between users, Predict content of interest to users successfully using not only the rating but also on user profile.	• There are other important user preferences that were not used.

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			Averaging (OWA) and Uninorm Aggregation Operators	operators called OWA and Uninorm. The model was integrated with HARMONISE platform in the Urban Resilience Domain in order to test the performance of the model.		● The system is applied to only urban resilience domain.
28.	Hybrid	(Kumar and Fan 2015)	Hybrid User-Item Based Collaborative Filtering	The paper proposes hybrid collaborative filtering method to recommend item to users. The paper uses Case Based Reasoning combined with average filling to overcome sparsity problem. To cluster the item, Self-Organising Map optimized with Genetic Algorithm was used.	Improved recommendation accuracy while addressing sparsity and scalability challenges of RS.	Only one dataset is used which is small.
29.	Hybrid	(Panigrahi, Lenka et al. 2016)	A Hybrid Distributed Collaborative Filtering Recommender Engine Using Apache Spark	The paper uses Alternating Least Square method for dimension reduction which is to overcome sparsity issue while K-means as a clustering technique is used to prevent scalability issue. The algorithm is written in Scala Programing Language while the implementation of the algorithm is	Overcome sparsity and scalability problem of CF RS.	Does not have the ability to update model whenever new user/item is added.

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				done using Apache Spark to provide parallel implementation.		
30.	Hybrid	(Callvik and Liu 2017)	Using Demographic Information to Reduce the New User Problem in Recommender Systems	Developed a framework using K-Means clustering and user demographic information to solve the new user problem. The research was evaluated using Movielens 100K dataset.	Overcome the problem of new user in RS.	• It uses solely demographic information which is not sufficient to capture new users. • The dataset is not sufficient to fully test the framework. Large dataset is required to do that.
31.	Hybrid	(Tarus, Niu et al. 2017)	A hybrid knowledge-based recommender system for e-learning based on ontology and sequential pattern mining	They proposed a hybrid knowledge-based recommender system based on ontology and sequential pattern mining (SPM) for recommendation of e-learning resources to learners. Ontology is used to represent knowledge about the learner and learning resources while SPM algorithm to discover learner's historical sequential learning patterns.	Better performance and accuracy as well as alleviating cold start and data sparsity.	The number of learning resources used is small. Large dataset need to be collected and used to fully test the RS.
32.	Hybrid	(Bagherifard, Rahmani et al. 2017)	Performance Improvement for Recommender Systems Using Ontology	They design heuristic hybrid recommender method which combine both memory and model based	Improve predictive accuracy and scalability of recommender system.	• Only k-means clustering techniques is used exclusively which is not efficient.

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				approach. Ontology is used specifically to improve accuracy of recommendation.		• Only movielens dataset is used for the research
33.	Hybrid	(Kermany and Alizadeh 2017)	A hybrid multi-criteria recommender system using ontology and neuro-fuzzy techniques	The research developed an enhanced multi-criteria recommender using neuro-fuzzy which combine demographic information and item based ontological information. They also combine fuzzy cosine and Jaccard similarity to calculate similarity.	Reduce sparsity and improved accuracy of prediction.	• Only one dataset is used for the research. • Does not consider new users in the research.
34.	Hybrid	(Nilashi, Ibrahim et al. 2018)	A recommender system based on collaborative filtering using ontology and dimensionality reduction techniques	They used ontology to improve the accuracy of recommendations in CF. They also used the dimensionality reduction technique, Singular Value Decomposition (SVD), to find the most similar items and users in each cluster of items and users.	Improve accuracy and overcome problem of data sparsity.	Scalability issue has not been implemented. EM Clustering cannot correctly find the complete structure of all data set. EM Clustering converge to local optima. The Matrix Factorization step is computationally highly intensive which makes it less scalable.
35.	Hybrid	(Kilani, Otoom et al. 2018)	A Genetic Algorithms-Based Hybrid Recommender System of Matrix Factorization and Neighborhood-	They build a novel genetic-based CF RS that hybridizes both the neighbourhood and the latent factor models to predict items for	Improved Navgaran et. al. RS in terms of MAE, precision and recall.	The dataset contain some unnecessary data that need to be excluded from the calculation of prediction of users/items.

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			Based Techniques	the active user. They then use the GA approach to recommend items for the active user in this hybrid model.		
36.	Hybrid	(Tewari and Barman 2018)	Sequencing of items in personalized recommendations using multiple recommendation techniques	Their approach generates recommendations by combining features of content based filtering, collaborative filtering, matrix factorization and opinion mining. The proposed RS dynamically keeps track of user's inclination towards different types of items with respect to time.	Generate top-N recommendation with high precision when compared with other traditional recommendation system. It also alleviate cold start and grey sheep problem.	In the recommendation there is no information concerning item. There should be ability to link user to another user so that trust among users can be established.
37.	Hybrid	(Palomares, Browne et al. 2018)	Multi-View Fuzzy Information Fusion in Collaborative Filtering Recommender Systems: Application to the Urban Resilience Domain	They proposed a hybrid framework which combines a collaborative filtering recommendation system with fuzzy decision-making approaches (based on the use of aggregation functions) to improve the accuracy of domain-specific recommendations.	Improve accuracy of domain specific recommendations and solve new user/cold user problem	Features such as inter-user trust is not captured in research. Weight modelling is lacking in the system. Issue of new item has not been captured by the system.
38.	Hybrid	(Chen, Hua et al. 2018)	A Hybrid Recommender System for Gaussian Mixture Model and	The research uses Gaussian Mixture Model and Matrix Factorization.	Overcome sparsity and improved accuracy of recommendation system.	• The GMMESMF need to be prepopulated. • Unrated ratings need to be filled

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			Enhanced Social Matrix Factorization Technology Based on Multiple Interests	Improved cosine is used to predict rating of unrated ratings of users. The Gaussian is used to cluster the ratings in order to reduce sparsity and matrix factorization is used for dimensionality reduction. They also used user and item social relationship to predict unrated ratings.		before prediction. ● There is high computational complexity with similarity due to too many users.
39.	Hybrid	(Da Costa, Manzato et al. 2019)	Boosting collaborative filtering with an ensemble of co-trained recommenders	They proposed an ensemble scheme based on a co-training approach (ECoRec), that drives two or more recommenders to agree with each other's predictions to generate their own.	Overcome the problem of Cold start and sparsity.	The performance of the system dropped in most database when the value of X>50.
40.	Hybrid	(Yan and Tang 2019)	Collaborative Filtering Based on Gaussian Mixture Model and Improved Jaccard Similarity	The research uses Gaussian mixture model for clustering in order to reduce sparsity and improved Jaccard similarity which combine Jaccard and Triangle similarity for similarity computation.	The result overcome sparsity and improved accuracy of rating prediction.	● The GMM has problem of convergence to local optima. ● Problem of parameter selection.
41.	Hybrid	(Natarajan, Vairavasundaram et al. 2020)	Resolving Data Sparsity and Cold	Uses recommender system with	Addresses cold start and sparsity issue of	Only DBpedia is used to acquire additional information

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			Start Problem in Collaborative Filtering Recommender System Using Linked Open Data	Linked Open Data to resolve cold start while sparsity is addressed using matrix factorisation with Linked Open Data.	recommendation system.	
42.	Hybrid	(Ghasemi and Momtazi 2021)	Neural text similarity of user reviews for improving collaborative filtering recommender systems	Develop a model for improving RS using user's ratings and reviews. Amazon ratings and review were used for the research.	Improved accuracy of RS	• Test implementation using other state of the earth dataset.

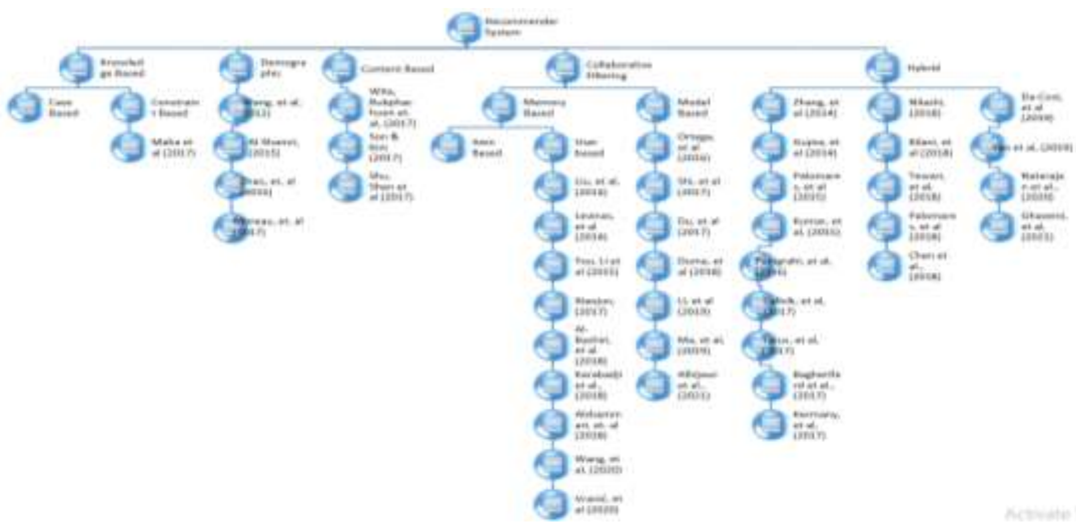

Figure 4: Taxonomy of Recommender System

Taxonomy of Recommender System:

The arrangement of concept into a form which provide clear knowledge of the categories is called taxonomy *(Gani, Siddiqa, Nasaruddin, 2015)*. In this literature we classify recommender system into 5 groups. They include; Knowledge Based, Demographic based, Content Based Filtering, Collaborative Filtering and Hybrid Recommender Systems. Figure 4 present the categorisation of recommender system which is studied in the survey. The taxonomy is presented to give insight into the different recommender system techniques and their behaviour. The figure indicates the different research papers used in this survey and the category they belong to. Looking at the knowledge based and demographic category, there are limited literature under this category.

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The categorisation provides more details into each category *(see Section 2.4)*. For instance, collaborative filtering has memory based and model based as its sub-category. The memory based is also broken down into item based and user based. While knowledge based has case based and constraint based as its sub-category. While the remaining types of RS do not have any sub-category.

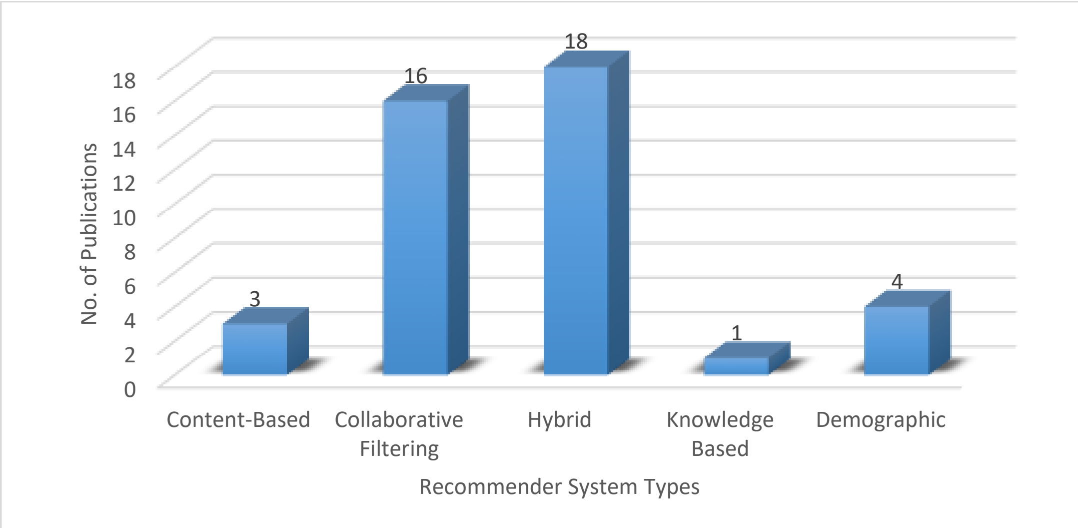

Figure 5: Chart Showing RS Method by No. of Publications

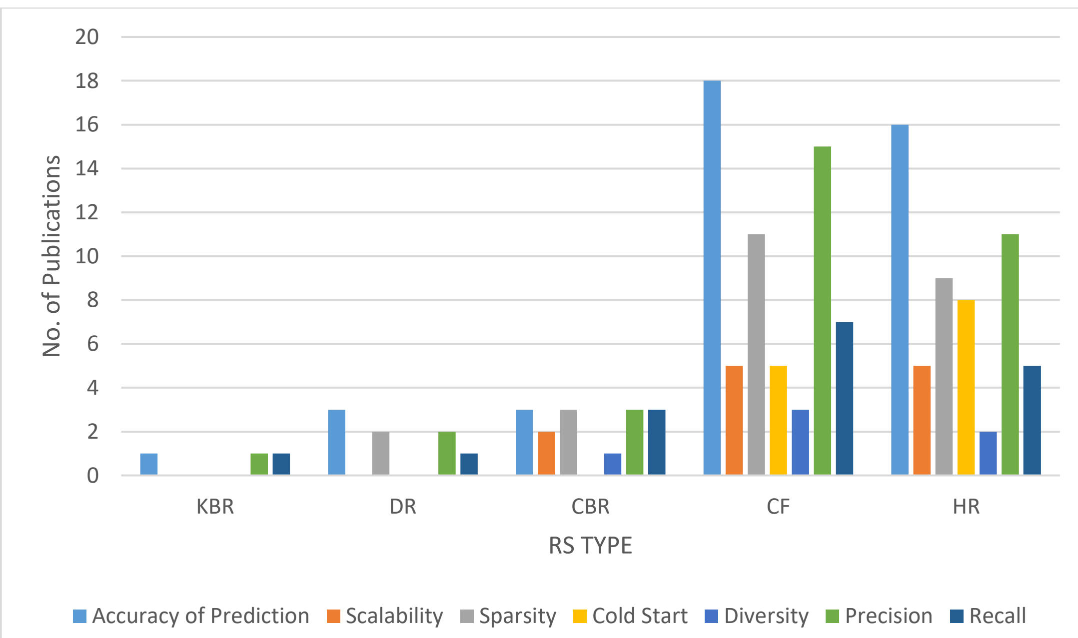

Figure 6: Chart Showing number of publications, their categorisation of RS methods based on requirements addressed

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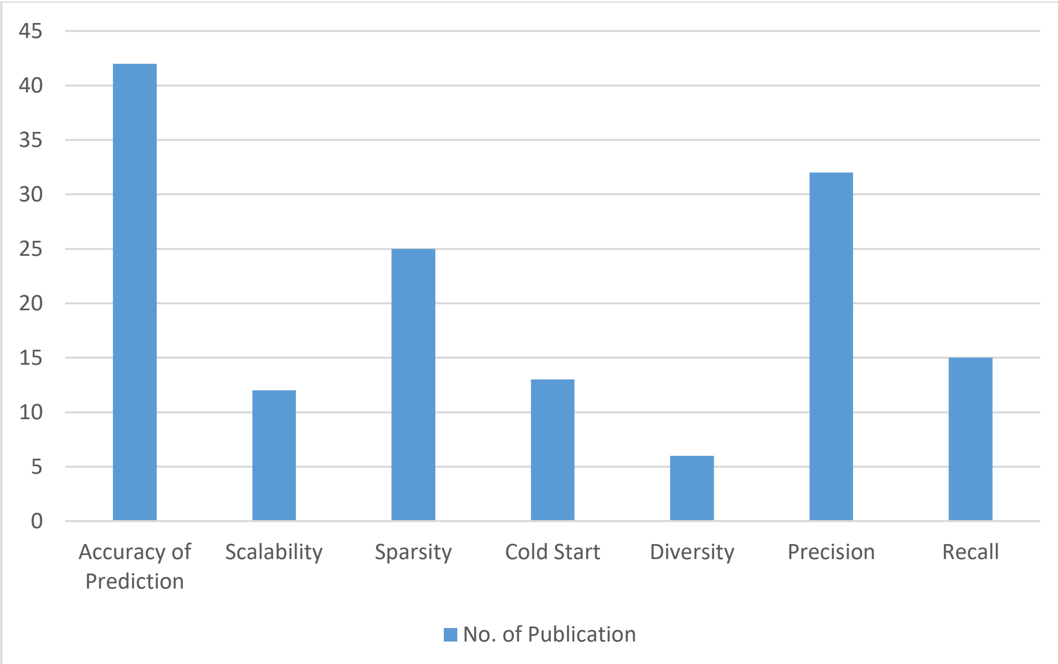

Figure 7:RS Requirements addressed in the Selected Papers

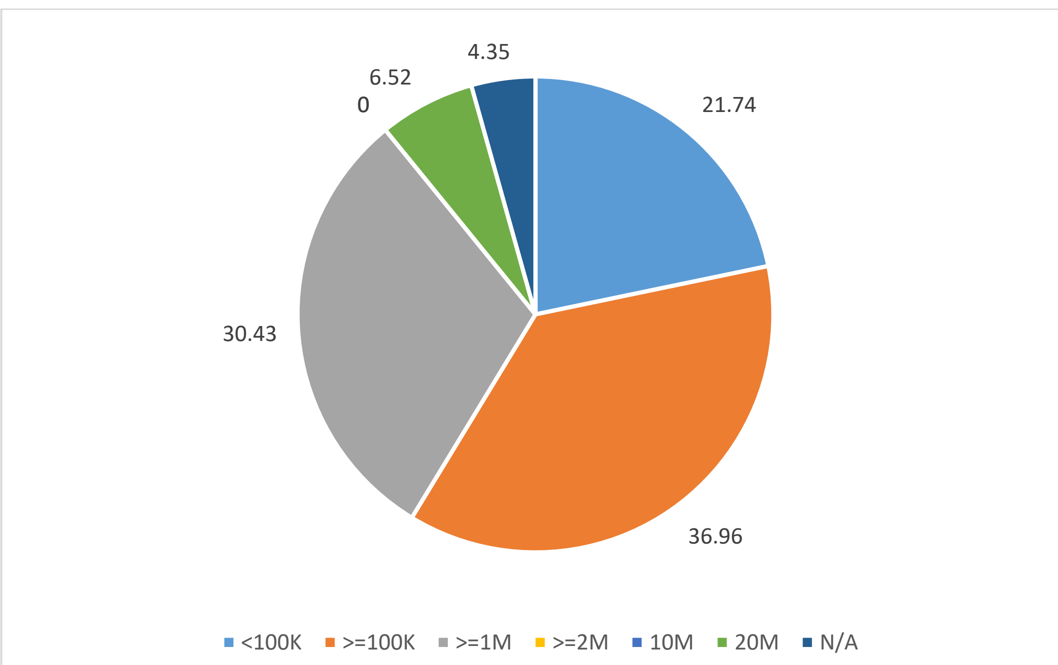

Figure 8: Percentage of Dataset range used in the Selected Papers

Table 3: Evaluation and Analysis of RS Techniques for Based on RS Requirements

S/N	RS Technique	Author(s)	RS Requirements						
			Accuracy of Prediction	Scalability	Sparsity	Cold Start/ New User	Diversity	Precision	Recall
1.	Knowledge Base	Maalej, et. al (2017)	√	×	×	×	×	√	√
2.	Demographic	Wang, et al, (2012)	√	×	×	×	×	×	×
3.		Al-Shamri, (2016)	√	N/A	√	×	N/A	N/A	N/A
4.		Zhao, et al, 2016	√	×	×	×	×	√	N/A
5.		Moreau, et al (2017)	×	N/A	√	×	N/A	√	√
6.	Content-Based	Wita, et al (2017)	√	×	√	×	√	√	√
7.		Son, et al (2017)	√	√	√	×	N/A	√	√
8.		Shu, et al (2017)	√	√	√	×	N/A	√	√
9.	CF (Memory Based)	Liu, et al. (2014)	√	×	√	√	N/A	√	√
10.		Levinas, et al, (2014)	√	×	√	×	N/A	√	×
11.		You, et al, (2015)	√	√	√	×	×	√	×
12.		Xiaojun, (2017)	√	√	√	×	N/A	√	√
13.		Al-Bashiri et. al., (2018)	√	×	√	×	×	√	√
14.		Karabadji, et al, (2018)	√	×	√	×	√	√	√
15.		Alshammaril, et al, (2018)	√	×	N/A	N/A	×	√	N/A
16.		Wang, et al, (2020)	√	×	×	×	×	×	×
17.		Vranić et al., 2020	√	×	×	×	×	√	√
18.	CF (Model Based)	Ortega, et al, (2016)	√	×	×	×	×	√	√
19.		Shi, et al, (2017)	√	×	√	×	√	√	×
20.		Du, et al, (2017)	√	×	√	√	×	×	N/A
21.		Duma & Twala, (2018)	√	√	×	×	×	√	×
22.		Li, Wang, (2017)	√	×	√	×	×	√	N/A
23.		Ma et al., 2019	√	√	√	×	×	×	×
24.		Alhijawi, et al, (2021)	√	N/A	√	√	N/A	√	N/A
25.	Hybrid	Zhang et. al., (2014)	√	×	×	√	√	√	×

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26.		Gupta, & Gadge, (2014)	√	√	×	√	×	×	×
27.		Palomares, et al, (2015)	√	×	√	×	√	×	N/A
28.		Kumar & Fan (2015)	√	√	√	×	×	√	√
29.		Panigrahi, P., et al (2016)	√	√	√	×	×	√	×
30.		Calvik & Liu, (2017)	√	×	×	√	×	×	×
31.		Tarus, et al, (2017)	√	×	√	√	×	√	√
32.		Bagherifard, et al, (2017)	√	√	N/A	√	N/A	√	√
33.		Kermany & Alizadeh, (2017)	√	×	√	×	N/A	√	√
34.		Nilashi, et al (2017)	√	√	√	×	N/A	√	×
35.		Kilani, et al, (2018)	√	×	×	×	√	√	N/A
36.		Tewari, & Barman, (2018)	√	×	×	√	×	√	√
37.		Palomares, et al, (2018)	√	×	×	√	×	√	N/A
38.		Chen, et al, (2018)	√	N/A	√	√	×	√	N/A
39.		da Costa, et al (2019)	√	N/A	√	√	N/A	√	×
40.		Yan & Tang, (2019)	√	×	√	×	N/A	N/A	N/A
41.		Natarajan, et al., (2020)	√	√	N/A	√	N/A	√	√
42.		Ghasemi & Momtazi (2021)	√	N/A	N/A	N/A	N/A	N/A	N/A

Discussion:

The research collected papers from renowned publications such as Springer, Elsevier, IEEE, etc. These papers collected, have high impact factor as well as sighted in many science journals. A total of 42 journals were selected and reviewed.

Results have shown that most papers have laid emphasis on Collaborative filtering and hybrid recommender system. Figure 5 shows that 3 papers were selected from CBR, 16 papers from collaborative filtering with model based having 7 and memory based 9 papers, 18 papers were from hybrid recommender system, 1 papers from KBR and 4 papers from DRS. These papers were selected from google scholar, researchgate and other search engine. The search was done using keyword related to area under study.

Table 1 shows the dataset used by the selected papers in order to test their work. These datasets were collected from among others the Grouplens research group at the University of Minnesota, Netflix, Book-Crossing, Yahoo Web Scope, etc. The papers were categorised into <100K, >=100K, >=1M, >=2M, 10M, and 20M dataset ranges. Figure 8 shows the percentages of the dataset used the selected papers as they appear in the papers. 4.35% of the papers used <100K dataset, 36.96% papers used >=100K data, 30.43% uses 1M data. 2M and 10M dataset were not used by any research paper while 20M dataset was used by only 4.35% of the papers. This analysis shows that majority of the papers use low volume dataset which is inadequate for today's research considering the large amount of data available in the e-commerce, social network, etc. To fully test the capability of a recommender system that will provide timely recommendation, it needs to be tested with a large volume of data. This will make it more robust, scalable and produce better recommendation that will be reliable.

The papers selected were subjected into detail review and analysis. Table 2, explore the methodology used by each paper, solution obtained, and the problems of the method. The review shows that the performance of the recommendation was enhance by combining multiple techniques such as CBR vs CFR, DR vs CFR to form a hybrid system. Further analysis shows that incorporating ensemble into the clustering and prediction steps will greatly improve the performance of the recommendation system.

Furthermore, based on the given RS requirements, recommendation can be studied and some input can be obtained that can improve the recommendation. Figure 6 shows that HRS address all the requirements and achieve better result on all the requirements except on the scalability and diversity. This achievement became possible as a result of the application of many RS techniques, AI algorithms and other features. Other reason for the success in the hybrid method is the appearance of ensemble techniques into the similarity computation, clustering and prediction. While the CFR achieve most of its success through the advancement in modelling and other machine learning techniques and application of feature selection into the recommendation. This reduces the features that are hidden in the dataset.

CBR method has been very effective in achieving accuracy, scalability, sparsity, precision and recall. The weakness of this approach is that addressing cold start is very poor. The DRS does not address the problem of cold start and diversity. While KBR has been found to be low in addressing scalability, sparsity and cold start. This can be attributed to low research in the area, authors pay less interest in addressing these requirements.

The research went ahead to combine the result of the analysis of the requirements into a single table. Figure 7, specifying that most papers pay more attention in addressing accuracy of prediction, precision, sparsity and recall while low attention is paid to addressing scalability, cold start and diversity.

Conclusion:

Recommender system has been a subject of discussion in the recent time in information retrieval. Study has been conducted into the categorisation and the requirements of RS. The main goal was to analyse the RS methods and requirements as well as to present the state-of-the-art RS techniques. This will provide researchers basis on improving the

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domain area and also provide support. The paper focuses more on the dataset used by the selected research papers, methodology employed, and problem of the methodology. The paper explores 7 requirements for RS such as Accuracy of prediction, scalability, sparsity, cold start, diversity, precision and recall. The outcome was that low dataset used by researchers in testing their algorithm brings about low performance of the RS. Also, HRS prove to be the best method of RS due to advancement of machine learning, and ensemble techniques.
Furthermore, most researchers focus more on addressing accuracy of prediction, sparsity, precision and recall. While less attention is given to other requirements such as scalability, cold start and diversity.
In future research, attention need to be given to other RS requirements such as scalability, cold start and diversity. Additionally, incorporating ensemble approach into the RS will bring about improve accuracy and enhance performance. Also, focus need to be paid to testing RS using large dataset.

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