A Study of Recent Recommender System Techniques

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A Study of Recent Recommender System Techniques

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ABSTRACT

The influx of data in most domains is huge and dynamic, leading to big data and hence the need to build a recommender system grows stronger. This work is a comprehensive survey of the current status of different recommendation approaches, their limitations and extension which when applied may eradicate incessant information overload problem of web entirely. Further, an investigation is conducted on the Google Scholar database delineating the temporal distribution of different recommendation techniques. Several most used and popular evaluation metrics, domain-specific application and data sets used in the recommendation are reviewed. By summarizing the current state-of-the-art, this work may help researchers in the field of recommendation system techniques and provides future directions highlighting issues that need to be focused and worked upon.

Keywords: Collaborative Filtering, Genetic Algorithm, Hybrid Approach, Evaluation metrics, Fuzzy, Group Recommender System, Cold-Start.

INTRODUCTION

Recommender system (RS) has emanated as the most popular application of big data (John Walker 2014; Livinus et al. 2016) that helps the user to find relevant information in the era of data deluge. As a result of the expansion in the e-commerce business, the customers (buyers) have to process a large amount of information before they decide to buy an item. RS provides the solution to this information overload problem as it is used to suggest products to the customers. It further enhances the e-commerce business since it helps to find the interesting things for the users which they may wish to purchase, however, did not come across things, due to information overload. RS is often used to improve customer's trust and loyalty as it provides unique personalized service to each customer. User interest may be determined in the following ways:

- By monitoring past buying behavior
- By directly asking user preferences

A formal definition of RS is as follows: Let U be the set of users and I be the set of items. We define a function F that quantifies the utility of item I ($\in$ I) to a user u ($\in$ U) by the mapping F: $U \times I \rightarrow R$ where R is defined as the set of ratings (Sarwar et al. 2000). The goal is to learn and use F to determine the rating of a previously unseen item i by user u in order to generate a possible set of recommended items.

Several traditional recommendation techniques include collaborative filtering (CF) (Ekstrand et al. 2011), Content-Based Recommender System (CBS) (Lops et al. 2011) and Hybrid Recommender System (Varshavsky et al. 2014). Each technique has its advantages and limitations; for example, domain free nature of CF has averted most research work from CBS (Ekstrand et al. 2011). However, CF suffers from cold start and sparsity problem (Hedge et al. 2015) while CBS suffers from overspecialization (Lops et al. 2011). Consider a case where a user is new to the system and the system does not have any information about the user. In such a case, drawing inference about user's preferences becomes difficult and a quality recommendation cannot be produced. Such a scenario occurs both in the case of novel users and new items and is a perfect example of a cold start problem which indirectly leads to sparsity problem. Many advanced techniques have been suggested for mitigating these limitations such as, social, interactive, deep learning, context-aware, and fuzzy logic-based RS which also increase coverage and accuracy. For recommending items to a group of users, group recommender system (GRS) came into picture which exploits individual contextual information, tastes and demographic information for developing suggestions (Boratto 2016). Various nature-inspired algorithms such as Cuckoo search (Tosun 2014), swarm optimization (Chen et al. 2012) and genetic algorithm (Whitley 1994) have been investigated by the researchers for accuracy and optimization of the system.

Several evaluation methods used for RS are Recall, Precision, F-measure, Mean absolute error (MAE), Coverage, Root Mean Square (RMSE), Sensitivity, Specificity and Receiver Operating Characteristics (ROC) (Franzen 2011). In order to analyze the system developed, an appropriate metric should be chosen taking into consideration the user perspective and purpose that needs to be fulfilled by the system. Therefore, to help the researchers understand the RS development from various aspects including evaluation metrics and datasets and to assist them, this paper reviews the RS from all aspects that need to be considered for its development.

In recent years, several survey papers have been published but none of the paper to best of our knowledge have considered every aspect of RS including approaches, application domain, evaluation metrics, and datasets at one place. For example, Jie Lu et al. (2015) in their work reviewed application development of RS categorizing into eight major domains. Herlocker et al. (2004) reviewed various evaluation metrics and focussed majorly on the user-centric evaluation of the system as a whole. Bobadilla et al. (2013) discussed evolution and overview of RS including the CF algorithm. It further provides the classification for these systems. Sharma et al. (2013) in their work classified RS into three major categories i.e., CF, CBS, and hybrid recommender system and discussed several challenges associated with them. Yera et al. (2017) investigated the use of fuzzy logic in the recommendation delineating various research gaps. They also collected several papers from Web of Science and studied the temporal distribution of papers, distinguishing them by journal and conference. Although several works have been published in the field of RS, none of the work has conducted a comprehensive review of the RS approaches and evaluation metrics.

The main contributions of this paper are:

1. This paper surveyed the different approaches of RS, evaluation metrics used by the researchers and datasets that have majorly been worked upon.
2. This paper statistically, perceptively and comprehensively summarizes and categorizes the RS into 8 major approaches including the advanced RS techniques such as social, genetic, fuzzy, context-aware and group RS.
3. Framework for each approach has been further carefully analyzed, delineating its contribution, shortcomings and motivating the researchers to further carry out the research work suggesting research directions in the area of RS.
4. Different evaluation metrics have been investigated with a view of studying metrics according to the purpose of the system, enlightening the user-centric direction for evaluating the system.
5. Further, it statistically summarizes various datasets that are widely being used to analyze the behavior of RS mentioning most widely used dataset and its reason.
6. Incorporating features mentioned in our study in current RS may prove to be a boon for many industries such as Flickr, Netflix and research community.

This paper describes several variants and extensions of RS. Survey of RS techniques along with its limitations is detailed in Section 2. Datasets and application of RS in various domains are discussed and analyzed in Section 3. Section 4 presents the statistical analysis of research work on RS during 2003-2017. Various metrics used for evaluation purposes are reviewed in Section 5. Section 6 discusses limitations and future work. Section 7 concludes the work.

RECOMMENDATION APPROACHES

This section presents the comprehensive review and challenges of different methodologies of RS, including traditional techniques such as collaborative filtering, content-based, hybrid method and recently investigated social-network, context-aware, group, fuzzy, interactive, deep learning and evolutionary methods such as genetic algorithm.

Content-Based Recommender System (CBS)

CBS described in (Breese et al. 1998) is based on the item's description and a profile of the user's preference. In order to generate recommendations using this technique, potential items are compared with the items that were rated by the user and matching of the items is determined. Consider movies data, for instance, the possible features of movies include - the genre, actors or orientation to children. Therefore, by matching user's interest and item features a possible set of recommended items is generated. In this technique, a user's interest is based on the features present in the objects the user has rated. Abbassi et al. (2009) present Outside-The-Box(OTB) recommendations by generating regions of items based on items' similarity and adherence of users to regions which overcomes chance in the system. This chance results from returning the items that are too similar to those previously rated by the user.

CBS suffers from a serious drawback of limited scope (Breese et al. 1998) since it can recommend items that are similar to the original seed which may not be surprising to the user, cannot deal with user's changing preference and further does not suggest "most popular products" to users. Moreover, naive user problem (Nilashi et al. 2018) exists where accurate items cannot be recommended to the user unless a sufficient number of items has been rated by the user in order to understand user's preference.

Collaborative Filtering (CF)

The basic idea behind this approach is that "if users shared the same interest in the past they will have a similar taste in the future". For example, if two users say X and Y have overlapping purchase history then if user X has purchased an item that user Y has not seen then, the idea is to recommend this purchased item to user Y as well. CF requires a large amount of information about user interests, behavior and activities in order to provide accurate recommendations which is not an ideal case since it suffers from the data sparsity problem, i.e., practically, RS is based on large dataset so user-item rating matrix would be large and sparse which leads to poor performance of the RS (Najafabadi et al. 2016).

CF systems can be characterized into two types according to Breese et al. (1998), namely, memory and model-based techniques. Memory-based techniques use ratings to compute the similarity between users and items and the computed similarity can further be used for making recommendations. These techniques are effective and easy to implement. Model-based techniques use data mining and machine learning algorithms to generate recommendations. Algorithms include associative rule mining, matrix factorization, Bayesian networks, etc. A major advantage of model-based over memory-based techniques is that it can handle sparsity problem better.

Matrix factorization as described by (Koren et al. 2009; Hernando et al. 2016) is the soul of CF which suffers from sparsity and cold-start problem. Graph-based algorithms (Chen et al. 2013; Lee & Lee 2015) are the heuristics that mitigate the effect of sparsity while recommending novel items keeping them relevant to users. Additionally, fake identity can be used to attack RS and enter abrupt data into the system which leads to the generation of inappropriate recommendations. Trust-Based techniques empower the RS to handle fake user and overcome sparsity as well as cold-start problem as described by Massa and Avesani (2007). Pheromone updating strategy of ants (Bedi et al. 2009) employed in generating recommendations overcomes overspecialization or serendipity where even items not rated well by a similar user but matched active user's interest are recommended.

CF is the most worked upon the area and several different techniques including kNN (Huynh et al. 2018), Normalized cut (Bellogin & Parapar 2012), Alternating least square (Chen et al. 2018) has been explored to generate accurate recommendations. Furthermore, as it is domain-free, once an algorithm has been generated can be applied on any dataset which is the sole reason for its success in the research world.

Hybrid Recommender System

From the above discussion, it can be inferred that the mentioned approaches have certain merits and demerits depending upon different scenarios. One solution is to consider the composition of different techniques to generate better recommendations. Recent research (Wang et al. 2004; Lu et al. 2013) combined CF and CBS approach in an attempt to reduce sparsity, scalability, cold-start problem and also to provide more accurate recommendations than the respective pure approaches. Nature inspired algorithm such as cuckoo search (Katarya & Verma 2017) and swarm optimization (Katarya & Verma 2018) when complemented with hybrid approach were used to improve the accuracy of the algorithm and showed significantly better results. In addition, observed in (Katarya & Verma 2017) that including contextual information (feedback time, location) further improved efficiency of the algorithm. Nilashi et al. (2018) suggested a hybrid method using dimensionality reduction and ontology which solved scalability and sparsity problem to some extent. Several different algorithms including clustering and 3A ranking algorithm have also been exploited to generate hybrid recommendations.

Netflix (2003) is an example that makes use of hybrid approach as recommendation list is generated by comparing searching and watching habits of similar users as well as by recommending movies that have similar features with movies that user has rated or liked.

Context-Aware Recommender System (CARS)

In some applications, such as movie recommendation, in addition to user-rating matrix companion information (kids, teenager, aged) if included will be supplementary and help to generate more accurate results. With CARS, instead of 2-dimensional rating matrix ($\mathrm{U} \times \mathrm{I}$), tensor of order 3 ($\mathrm{U}\times\mathrm{I}\times\mathrm{C}$) where $\mathrm{U} \in$ Users, $\mathrm{I} \in$ Items and $\mathrm{C} \in$ contextual information comes into play. Here, contextual information refers to any information about the situation or entity such as geographical, demographical, temporal or any other information. Due to different domains of contextual information, proper representation of contextual information needs to be done. Adomavicius and Tuzhilin (2011) proposed three different algorithmic paradigms for incorporating contextual information in RS namely, contextual pre-filtering, post-filtering, and modeling.

Valid context description according to the situation, dynamic user preferences and availability of only two public datasets (Moviepilot and Filmtipset) were some challenges of CARS discussed in (Yujie & Licai 2010; Said et al. 2011). Moreover, with the introduction of another dimension, data sparsity and scalability problem further get intensified. This massive data storage and computation can be worked upon using cloud computing (Marston et al. 2011) taking into consideration the privacy and security of users(Si & Li 2018).

Social Network-Based Recommender System (SNRS)

With the advent of Social Network and multifaceted user’s life, SNRS marked a dramatic growth in recent years. In SNRS, the user has a dual profile, i.e., it contains the user's own data and social connection data. By exploiting social information such as social tagging, bookmarks, co-authorships, trust (online friending, comments, social tagging), an opportunity for a system whose data is too sparse and is incapable of finding similar users is being offered. There also arises a case where a user can enter abrupt data in the database by faking his identity, for such cases trust-based recommender system has been widely discussed by the researchers which further increase accuracy and coverage of system (Yang et al. 2014). Additionally, user can trust different friends in different domain, for instance, user can have similar movie taste but conflicting research taste. For such cases, category specific circles of friends need to be generated and worked upon. SRS based on “co-citation” was developed by Shiratsuchi et al. (2006) where weights of the social relationship between users were the number of “co-cited” bookmarks. Song et al. (2011) proposed a health social network system for people with a chronic health condition to find patients who can help each other.

CF-based social RS was primarily divided into two main categories: Matrix factorization-based and nearest neighborhood-based recommender system in (Yang et al. 2014). Matrix factorization-based RS is further split into Social Recommendation (SoRec), Social trust ensemble (STE), Social matrix factorization model and Circle-based recommendation. Nearest neighborhood-based RS is split into trust-based, Bayesian inference based, trust walker and trust CF. El-korany and Khatab (2012) further claimed that matrix factorization based RS outperforms the nearest neighborhood-based RS but lacks in the easiness of implementation. Further, ontology-based RS whose basis was the integration of content and collaborative filtering was proposed by El-korany and Khatab (2012).

Due to huge data flow on the social network, representing data flexibly and user's privacy is the main concern (Bansal & Baliyan 2019). Future of SRS lies in parallel computing platform such as Hadoop (Zikopoulos & Eaton 2011) in order to reduce the dimensionality and redundancy of data and improve real-time user experience.

Group Recommender System (GRS)

GRS is an information filtering tool that aids a group of users when face-to-face interaction is not possible and users have to consume items with each other (Cantador et al. 2012). For instance, planning a dinner or a vacation. While fostering suggestion for a group, certain factors such as social dynamics, accessibility, and affordability of individual, user’s demographic classification, trust among group members (Quijano-Sanchez et al. 2013) and places they visited in former trips in case of e-tourism (Garcia et al. 2011) needs to be considered. Different techniques have been used by researchers to capture individual preferences of the group member. The conversational approach is one such technique where users can interactively engage in steering recommendations. Two conversational approaches were discussed in (Nguyen & Ricci 2018), namely critiquing (McCarthy et al. 2006) which uses session-specific user's feedback on suggested items and case-study (McCarthy et al. 2006) exploits reactive and pro-active suggestions based on user-feedback in form of critiques. In addition to this McCarthy et al. (2006), discussed how synchronous communication can be used for getting assistance for a skiing vacation. For users who were not able to communicate synchronously, collaborate communication by using facial expression, speech and gesture to the current recommendation was used in (Jameson et al. 2004) for a travel recommender system. An asynchronous model of group recommendation was developed by McCarthy et al. (2006) allowing a group of users to engage in a web-based interface. Christensen and Schiaffino (2011) discussed three methods, merging recommendation made for an individual, aggregation of individual rating and construction of group preference model for generating recommendations for movie and music.

Despite many types of research, GRS suffers from all challenges mentioned in the above discussed approaches such as cold-start, sparsity, privacy and more advanced challenges such as evolving individual preferences with time and situation, user profile scarcity and finding more suitable elicitation and aggregation methods (Jameson 2004). In case a user wants to go for a solo trip, strategy to automatically find communities of interest will be useful. Future of GRS lies in implementing a domain-free system that is both a facilitator to help a group reach to a decision and a mediator by suggesting items that are accepted by the entire group while preserving user’s privacy.

Genetic Algorithm Based Recommender System (GARS)

Genetic Algorithm (GA) is an evolutionary approach which is applied for optimization of the objective function. In GA, problem coded as a string is called chromosome, and a set of solution candidates is called population on which selection strategy is applied to choose a better evolving solution. GARS though optimal is stochastic in nature (Pandian & Modrák 2009), i.e., optimality is not guaranteed. GA is used in RS for mainly two purposes: optimizing similarity function (Bobadilla et al. 2011) and clustering (Kim and Ahn 2008). Bobadilla et al. (2011) in his work examined and observed GA metric to run 42% faster than the correlation. A hybrid model based GA implemented on MovieLens dataset was proposed in (Gao & Li 2008) and proved to be efficient than the conventional model. Another GARS was proposed in [34] using GA k-means on online shopping market which also proved to be more accurate and productive than the standard clustering algorithm and whose efficiency can be further improved by proposing a method for fixing k instead of taking it randomly.

Most researches till today on GARS have utilized ratings of users which is the least possible information in any recommender system. Investigation on GARS in spite of showing significant results has not yet been done on a greater scale due to its resilient implementation, stochastic nature, and sensitivity to the initial population (Gao & Li 2008). Repeated calculation of fitness function to reach optimality makes it the most expensive and resource consuming RS. Moreover, the nature of GA works in its disadvantage and may even find a solution that does not exist in reality (Pandian & Modrák 2009).

Fuzzy Logic Based Recommender System (FRS)

FRS is information filtering application which handles and optimizes the effect of natural noise such as impreciseness, uncertainty in user preferences, vagueness in item features and user's behavior and thus proves to be a breakthrough to the world (Yera et al. 2016). Yager (2003) found FRS to be complementary to CF rather than competitive as it uses the same similarity measures as used by traditional approaches but uses fuzzy set to represent items. Investigation depicts that using fuzzy logic in RS, objects are represented using primitive assertions and with each assertion is associated a value which depicts the degree to which assertion is correct. Some related assertions are combined using attributes or features. Further, while making suggestions dynamic user preference and user's choice of which attributes are more important to him are incorporated using fuzzy logic which was not taken care of in traditional methods (Jain & Gupta 2018). Serrano-Guerrero et al. (2011) used Google wave and developed a linguistic fuzzy recommender system to assist users when the number of resources and users are high. To make such a system more effective users' activities can be captured within each wave.

Items or user profiles which often present complicated tree structures in the business application were modeled by fuzzy tree structure more flexibly (Wu et al. 2015). Ghavipour et al. (2016) in his work proposed a continuous action-set learning automaton (CALA) based method to adjust membership function of fuzzy trust and distrust considering trust relationship changes and preferences which alleviated cold start and sparsity problem. A medical diagnosis intuitionistic fuzzy recommender (Thong 2015) and fashion recommender (Wang et al. 2015) that incorporates human perception and emotion using intelligent techniques such as fuzzy decision tree were discussed showing its application in different domains. Some researchers have also tried their hand with clustering in FRS. One such fuzzy c-means approach was discussed in (Koohi et al. 2016) which outperformed traditional clustering approach.

Fuzzy logic in complement with CF and soft computing is gathering great attention. The future of FRS lies in applying fuzzy logic to manage natural noise in other RS techniques such as group, context-aware and hybrid recommender system and developing an accurate, optimized system that should be capable of tackling both small and large data sets. Research works on FRS though have witnessed a major boost, yet lack suitable data sets for their evaluation.

Deep Learning Based Recommender System (DLRS)

Deep learning in RS has garnered considerable interest in recent years owing not only to deep feature learning, inherent feature extraction, abstraction within data but also to its excellent performance in terms of accuracy. Capturing non-linear, non-trivial user/item relationship or any intrinsic relation that exists within data sources such as contextual and visual information justifies the capability and great use of deep learning in a recommendation engine. Convington et al. (2016) presented a DLRS for YouTube. Various deep learning techniques for generating recommendations exist which are applied depending upon the system's requirement. The multilayer perceptron is one such technique using which nonlinear transformation can be added to generate recommendations, interpreting it into neural extension. Guo et al. (2017) introduced deep factorization which integrates high order feature via deep neural network and low order feature interaction via factorization machines. Autoencoder is another unsupervised technique which is either used to fill the blanks of a matrix in reconstruction layer or to learn lower dimensional feature extraction. Convolution technique of neural network with pool operation can be used for image feature extraction (Wang et al. 2017), text feature extraction (Zheng et al. 2017), audio and video feature extraction (Van den Oord et al. 2013). Some applications do not require users to log-in in order to generate recommendation but instead use cookies or session information. However, such a mechanism does not generate trusted recommendations due to extreme sparsity present. Recurrent neural network (RNN) is one such technique that solves this issue by remembering former computation and modeling suitable data (Wu et al. 2016; Tan et al. 2016; Hidasi et al. 2015). Salakhutdinov et al. (2007) proposed RS based on Restricted Boltzmann which is to the best of our knowledge also the first recommendation model using a neural network. Attention model and reinforcement learning are another emerging trends in DLRS due to its capability of filtering out uninformative feature and noise from visual raw data, capturing user's temporal dynamics and providing timely feedback respectively. Additionally, in order to develop more powerful and expressive models, different deep learning techniques can be integrated resulting in a deep hybrid model for the recommendation. Zhang et al.

(2016) integrated convolution and autoencoder techniques for feature extraction of visual images. (Zhang et al. 2017; Lee et al. 2016) integrated convolution with RNN to develop quote and hashtag recommendations.

Despite the huge success of deep learning in RS, it still behaves like a “black box” limiting the explainability of hidden layers. Also, a huge amount of data is required by deep learning techniques to fully execute its parameters which results in scalability and time complexity problem. Going deeper in the context of deep learning, providing reasoning for the same and avoiding fake user profiles are other hurdles scientists have to cross. Another area that needs exploration on a large scale is multitask learning ranging from NLP to computer vision which can alleviate sparsity by providing implicit data augmentation.

Interactive Recommender System (IRS)

With the ubiquitous nature of RS, besides the accuracy of the algorithm human-RS interaction plays a crucial role in achieving user trust, transparency, and sense of control. IRS is one such system which breaks the "black-hole" nature of RS and let the user interact with the system resulting in increased transparency. Bostandjiev et al. (2012) maintained the transparency in the system by explaining the provenance of the suggested item and running a feedback loop to provide more relevant recommendations. It also allows the users to disclose information according to their wish and thus respecting their privacy. IRS in addition to providing explanatory interface also overcome the problem of fake and redundant profile as users can choose neighbors according to their choice. O'Donovan et al. (2008) presented PeerChooser, a visual IRS allowing the users to tweak the neighborhood graph depending upon their current mood and requirement. This approach further overcomes "grey-sheep" problem that exists in the graph. (Bodaghi & Homayounvala 2018) to improve the recommendation process adopted the user's interaction with the system depending upon their experience and skill level. Based on the interaction with the system, users were grouped into expert and novice depending upon their task completion skill as disclosing more about the system to all users may appear cumbersome for some. Additionally, learning about user’s choice from multiple social mediums and web resources such as facebook and twitter instead of one adds an advantage to the recommendation process. Tailoring the recommendation to match the user's changing preference and context is another topic that needs the researcher's attention. (Mahmood and Ricci 2007; Hariri et al. 2014) presented a multi-armed bandit algorithm which takes context information of users during the interaction session.

Future aspects involve considering and overcoming cold-start, diversity and serendipity problem in addition to providing interactive session to users. During the interactive session, both, novice as well as expert users, exists. So, there is a need to maintain type and control level of interaction as advanced visualization may be too complex for a wide audience. Hybridization of deep learning techniques with IRS marks another interesting area that needs the researcher's attention.

DATASETS AND RELATED DOMAINS DESCRIPTION

This section analyses the application of RS in various datasets and domains used for its evaluation. Primary research was conducted on Lu et al. (2015) to study the domain-specific application of RS ranging from e-government, e-commerce to e-group activity as shown in Figure 1. While each domain uses RS to a great extent, it would be interesting to note that e-resource shows the highest use of RS, with e-group activity showing the second highest use while e-library the least use. With the establishment of e-tourism companies such as Trivago of which maximum revenue is due to the recommendation, RS plays a major role in recommending places to tourists depending upon their budget, climate, etc. This has resulted in the increased investigation of RS in e-tourism making it the third highest application domain of RS. Table 1 defines the domain-specific application of RS.

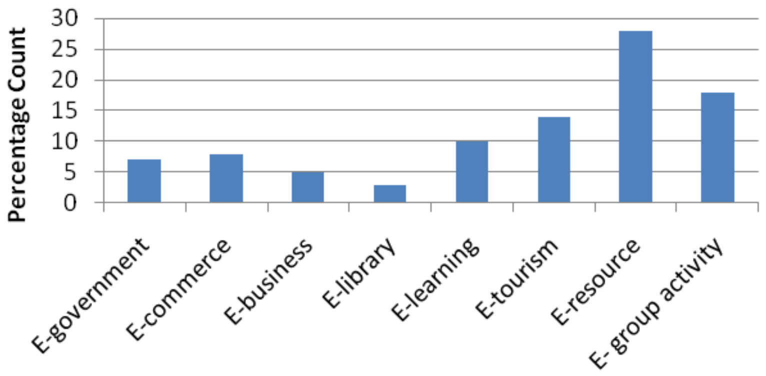

Figure 1. Application of Recommender System in Various Domains

Table 1. Description of Domains

Domain Name	Description
E-government	Provides public services to people in a country via electronic devices using internet
E-commerce	Trading i.e., buying and selling of services and goods via electronic medium using the internet
E-business	Conducting business using internet, intranet, extranet or some combination
E-library	Provides functions not only limited to reading books online but also learning the material in the form of audio, video
E-learning	Deliver course, program or degree via electronic medium using internet
E-tourism	Applying e-commerce in travel, tourism or catering i.e., providing these services online
E-resource	Accessing material such as journals electronically
E-group activity	Conducting group activity electronically such as group chat

Public datasets are being used to facilitate the investigation of various algorithms being thrived by the researchers. Using these open datasets, techniques fostered by scientists can be validated and improved. Primary research was conducted on 108 research papers retrieved from the Google Scholar database in November 2018 to study various data sets on which different approaches of RS have been applied. Different versions of the same dataset have been considered as the same dataset for the ease of study. Figure 2 shows the result of this investigation by plotting the percentage contribution of use of different data sets namely, MovieLens (2003), Amazon (2011), Jester (2003), Epinions (2014), Last.fm (2011), Microsoft Academic Search (2013), Netflix (2003), flixter (2010), Yahoo! Webscope (2015), Film Affinity (2016) and Movie Tweeting (2014) in research field of recommender system. However, it was found that most research work has been centered about movies data set due to its ease of availability and use.

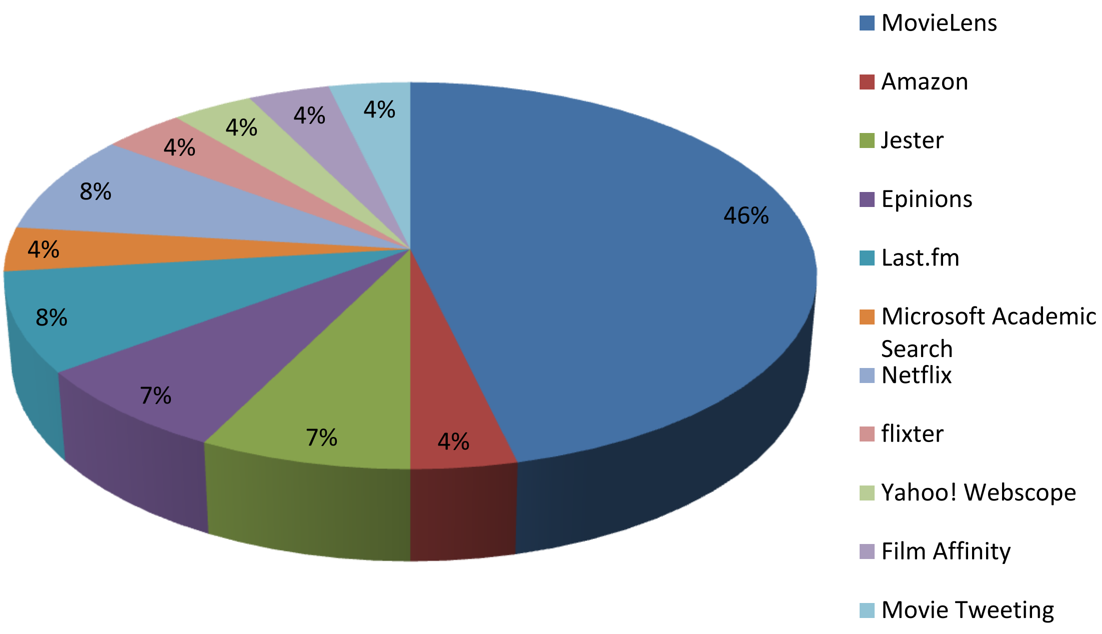

Figure 2. Percentage contribution of different data sets in RS research

METRICS OF RECOMMENDER SYSTEM

Majority of research to date on RS has focused on its accuracy and usefulness. To evaluate system's accuracy and usefulness, several metrics in the area of information retrieval are used to measure how close ranking of items predicted by the proposed system is to the true ranking of items according to user's preference and further to measure the usefulness of recommended items to the user. Choosing appropriate evaluation metrics to measure the effectiveness of RS helps scientists to provide several different solutions for the same problem and selecting the most promising solution amongst them.

Several standard metrics have been in use and most popular ones have been discussed in this section. Table 2 lists the symbols and their descriptions.

Table 2. Description of symbols

Symbol	Description
p_i	Predicted rating
q_i	True rating
N_s	Number of unexpected items
R	Number of recommendations generated by the system
PR	Number of recommendation generated by the prediction model
$u(R_i)$	The usefulness of item R_i
N_p	Number of items for which predictions can be

Most popular metrics used in the field of RS are accuracy prediction metrics i.e. MAE and RMSE which have been defined to measure the deviation between the predicted rating and user's true rating and measures the overall accuracy of the system by computing the average prediction error (Shani & Gunawardana 2011). Equations for evaluating MAE and RMSE are shown in Eq (1) and Eq (2).

$$\text{MAE}= \sum_{i=1}^{N} |p_i - q_i| / N \tag{1}$$

$$\text{RMSE}=\sqrt{1/N \sum_{i=1}^{N} (p_i - q_i)^2} \tag{2}$$

RMSE is similar to MAE but places more focus on larger deviation by penalizing the large errors by squaring them before being averaged. Though both RMSE and MAE are negatively-oriented (Bellogin et al. 2011), RMSE is always ≥ MAE and will be equal in the case where all errors have the same magnitude. Furthermore, in cases where an error of 20 is considered as bad as the error of 10, MAE is used over RMSE. However, if an error of 20 is considered more than twice as bad as error of 10, an error is further penalized by squaring it and RMSE rules over MAE.

In cases where the top-N list is returned, it may be unimportant to consider the accuracy of items that user have no interest in. For such cases, classification accuracy metrics, i.e., precision and recall proved to be useful (Herlocker et al. 2004).

Precision and recall were proposed by Cleverdon (1968) and is useful for measuring the relevance of the system (McNee et al. 2006). Precision is the ratio of relevant recommended items to the recommended items, shown in Eq (3)

$$\text{Precision} = \frac{\mathrm{N_{rc}}}{\mathrm{N_c}} \tag{3}$$

where $\mathrm{N_{rc}}$ and $\mathrm{N_c}$ have related meaning as shown in Table 3. Precision defines the relevance of the curated item. For example, suppose 10 items are recommended, amongst them, we say items that have a rating greater than 3.5 are relevant items and let the number of recommended items that are relevant be 4. Hence, precision here will be 0.4 or 40%. A recall is the ratio of relevant recommended items to the relevant items (Bellogin et al. 2011), shown in Eq (4)

$$\text{Recall} = \frac{\mathrm{N_{rc}}}{\mathrm{N_r}} \tag{4}$$

It gives the proposition that the curated item is relevant. There exists an inverse relationship between precision and recall. Higher the precision means more relevant items are returned than irrelevant ones without saying anything about whether all the relevant items are being retrieved and higher value of recall means most of the relevant items have been returned without saying anything about the number of irrelevant items returned. A drawback of classification accuracy metric as described in Table 4 can be solved by using accuracy, shown in Eq (5), as it covers all the cases examined.

$$\text{Accuracy} = \frac{N_{rc} + N_{ic}}{N} \tag{5}$$

F-measure defines the trade-off between recall and precision by taking the harmonic mean and now the goal is to maximize it as it measures precision and recall equally, shown in Eq (6)

$$\text{Fmeasure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

Table 3. Representation of symbols

	Curated	Un-curated	Total
Relevant	$\mathrm{N_{rc}}$	$\mathrm{N_{ru}}$	$\mathrm{N_r}$
Irrelevant	$\mathrm{N_{ic}}$	$\mathrm{N_{iu}}$	$\mathrm{N_i}$
Total	$\mathrm{N_c}$	$\mathrm{N_u}$	N

Serendipity and coverage are the two measures described in (Ge et al. 2010) which can be used to measure the usefulness of items to users. Coverage is the indicator of quality which concerns the degree to which set of items is considered while generating recommendations. According to (Ge et al. 2010), coverage is defined as a measure of the domain of recommendations over which system can make predictions, as shown in Eq (7)

$$\text{Coverage} = \frac{N_p}{N} \quad (7)$$

where N_p is the number of items for which predictions can be made and N is the number of available items.
There exist cases where a user might not have knowledge about an item but it fits the user's lifestyle. Serendipity is one such measure that concerns the novelty of the system and computes the degree to which recommended items attracts and excites the user (McNee et al. 2006). Serendipity is defined as follows in (Ge et al. 2010).

$$\text{Serendipity} = \frac{\sum_{i=1}^{N_s} u(R_i)}{N_s} \quad (8)$$

where $$N_s = \frac{R}{PR} \quad (9)$$

Increase in coverage does not lead to an increase in serendipity, however, higher serendipity leads to higher coverage(Ge et al. 2010).

Schein et al. (2002) suggested other metrics, namely, sensitivity, specificity, and ROC to evaluate RS. It graphically represents the trade-off between sensitivity and 1-specificity which measures the extent to which relevant and irrelevant items can be differentiated by the system. In the case of ROC, top-N items are selected by using a cut-off z_c where all items ranked above z_c are recommended (Herlocker et al. 2004). The curve is plotted by taking different values of z_c which result in further variation of sensitivity and specificity. ROC is analogous to precision-recall curve where sensitivity is the same as recall and is preferred over precision-recall when N_{iu} is valuable and should be used in the evaluation. Sensitivity is the probability of items recommended having high relevance with the active user. Specificity, shown in Eq (10) is defined as the probability of items not recommended given that they have low relevance with the active user.

$$\text{Specificity} = \frac{N_{iu} - N_{ic}}{N_{iu}} \quad (10)$$

Strength and weakness of different metrics are discussed in Table 4.

Table 4. Strength and weakness of evaluation metrics

Evaluation Metric	Range	Advantage	Disadvantage
Precision and Recall	(0-1) 1. Precision = 1 means each item retrieved was relevant. 2. Recall = 1 signifies all relevant items were retrieved. Nothing can be said about how many irrelevant items were retrieved.	1.A measure of relevance. 2. More comprehensive.	1. Need to convert ratings to binary-scale ratings. 2. Ignore N_{iu} cells.
MAE and RMSE	(0- ∞) Here, 0 indicates no error in the system, i.e., an ideal case	Easy and simple to understand.	Less appropriate when Top-N list is returned by the system
Coverage and Serendipity	(0-1) 1. Coverage = 1 means the entire set of items was covered while predicting. 2. Serendipity = 1 means the entire set of unexpected items proved to be useful.	Measures usefulness of items to users	Does not takes care of the accuracy of the system
ROC	(0-1) Value of 1 means ideal classifier	1. Output single number representing the overall performance of the system 2. Consider different length's recommendation lists	1. Requires large data set to distinguish between relevance and irrelevance. 2. The ordering among relevant items have no effect on ROC

Finally, an appropriate metric should be selected for evaluating the proposed system by the researchers taking into consideration the user-centric view, requirement and the purpose that needs to be fulfilled by the system.

SURVEY METHODOLOGY AND ANALYSIS

This section presents the statistical analysis of the research work on Recommender System during 2003-2017. Data were retrieved and analyzed from Google Scholar in November 2018, taking advantage of its generic nature, wide acceptance and easy accessibility in order to investigate the temporal growth of different recommendation techniques. The increasing interest of scientists in RS may be visualized through Figure3. Advanced search of Google Scholar was used to compute the increasing interest of scientists. Keywords used were "recommended" or "recommendation" matching the exact phrase found in the title of published work for the particular year. Research papers that have matching keywords in the title were only considered for analysis as matching keywords that appear in the abstract or anywhere else in the paper may lead to consideration of research work irrelevant to the topic and thus generating vagueness in the analysis. Figure 3 depicts research work on RS decreased slightly in the year 2005 reaching almost the same count as in the year 2003 but from then showed the ever-increasing interest of scientists till the year 2017 and now. RS has played a major role in increasing the revenue of big companies such as Amazon, Netflix, YouTube, Trivago and many more. 80% of movies watched by users on Netflix (Gomez-Uribe and Hunt 2016) and 60% of videos watched on YouTube are recommended ones (Davidson et al. 2010). This has been the major reason for ever increasing research and interest of scientists in the field of RS since 2003.

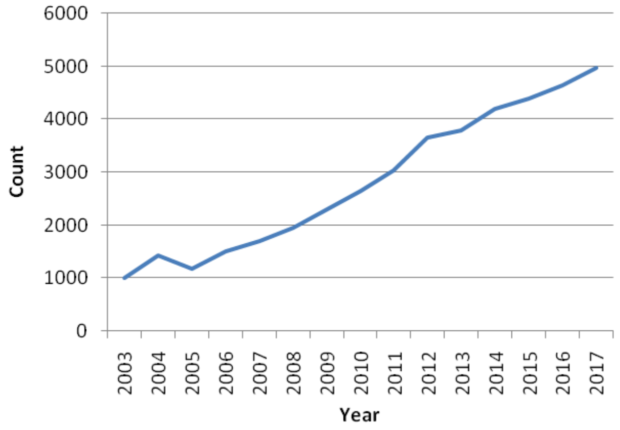

Figure 3. Temporal distribution of published research work on RS

Figure 4 shows the manual procedure adopted to conduct the survey for Figure 5- Figure 14.

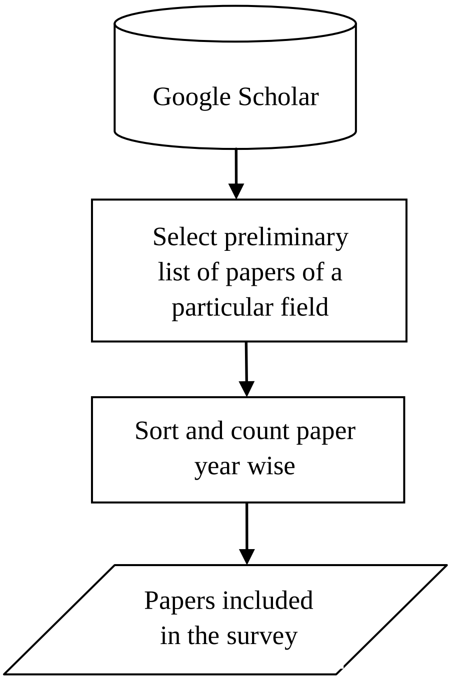

Figure 4. Investigation Methodology

Each step of the investigation methodology is detailed :

1. The advanced search option of Google Scholar has been used to conduct the survey.
2. Published research papers of the particular technique say content-based were computed by matching technique name using "exact phrase" option available and using keywords "recommended" or "recommendation" in the "at least one of the words" field available.
3. Year range was customized to find the count of research papers published in a specific year of specified technique.
4. Finally, graphs were plotted based on results obtained from the advanced search option of Google Scholar.

Specifically, the query executed to find the growing research in different recommendation techniques was "Technique name" and "recommender or recommendation". For instance, results for context-aware recommender system were elicited based on keywords "context-aware" and "recommender or recommendation" found in the title of the published research work. Figures 5-14 shows the growth pattern of research work in different recommendation techniques.

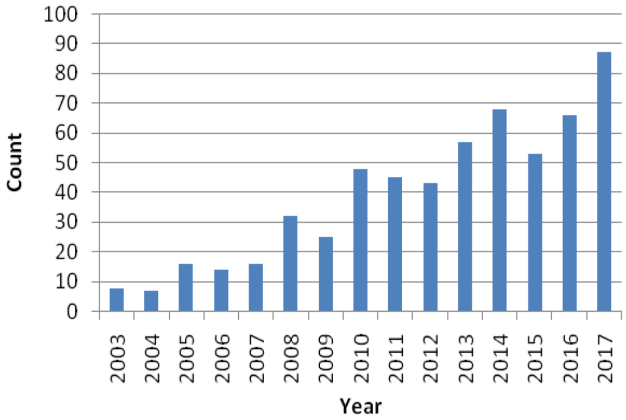

Figure 5. Temporal distribution of CBS

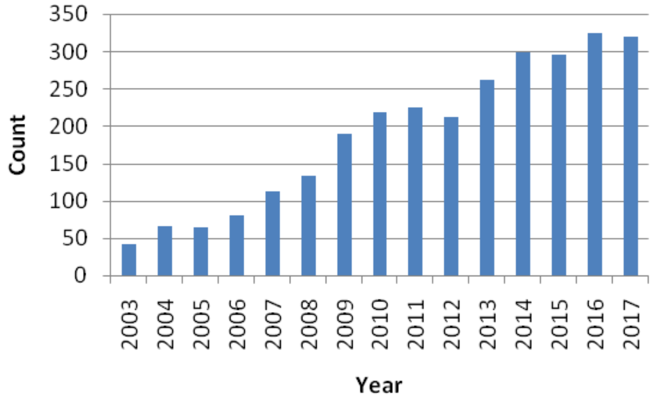

Figure 6. Temporal distribution of CF

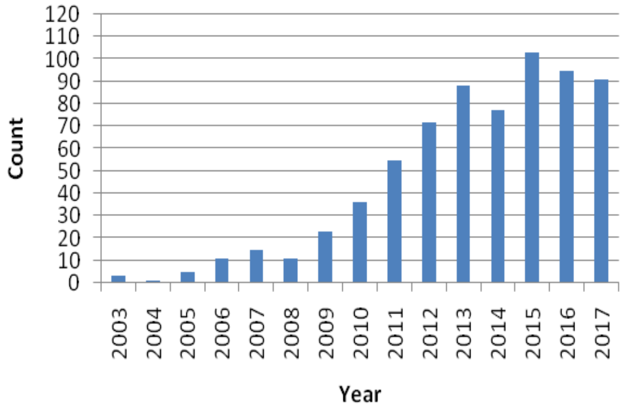

Figure 7. Temporal distribution of CARS

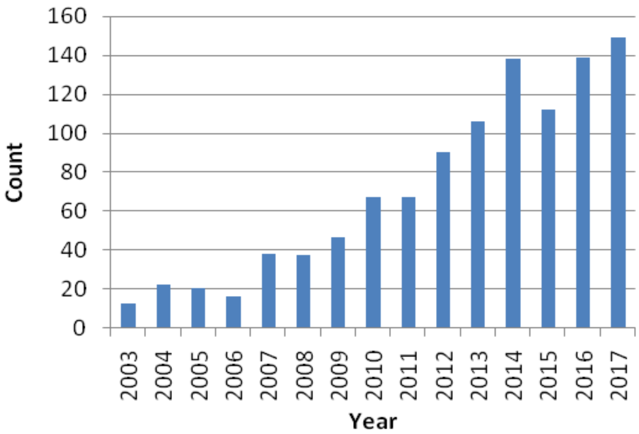

Figure 8. Temporal distribution of Hybrid RS

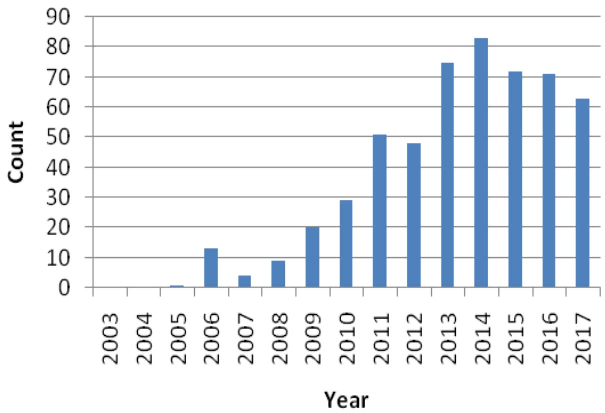

Figure 9. Temporal distribution of SNRS

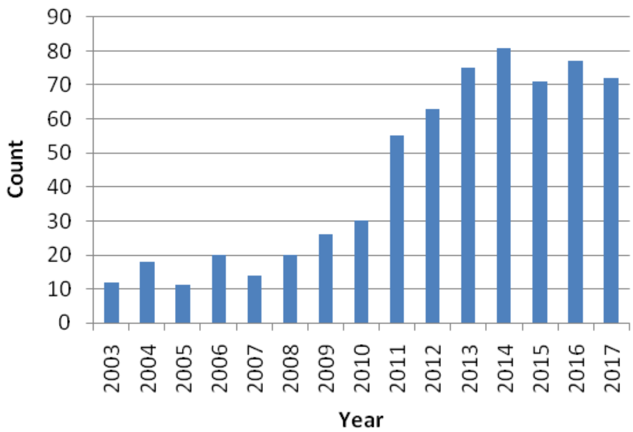

Figure 10. Temporal distribution of GRS

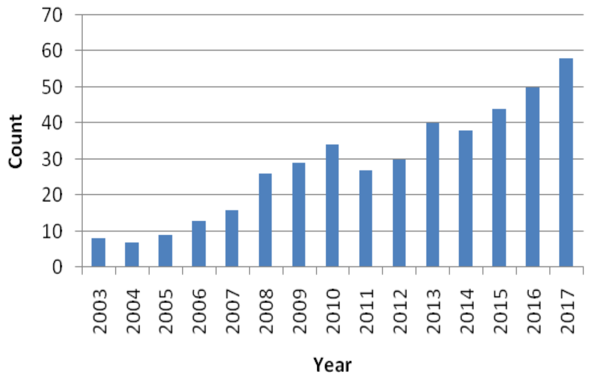

Figure 11. Temporal distribution of FRS

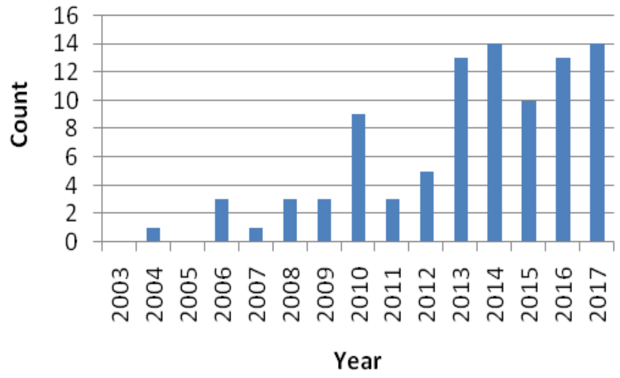

Figure 12. Temporal distribution of GARS

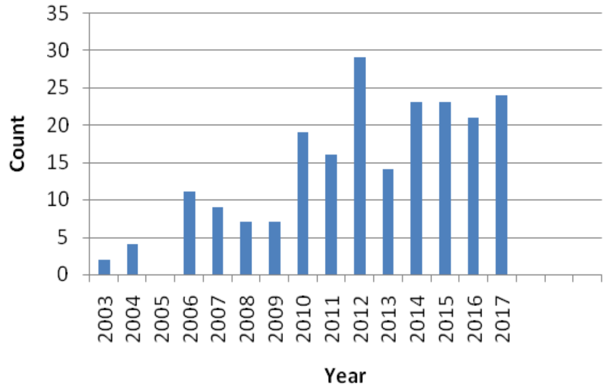

Figure 13. Temporal distribution of IRS

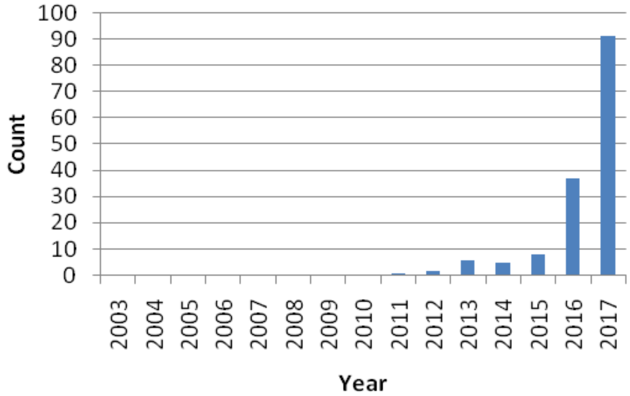

Figure 14. Temporal distribution of DLRS

From Figure 5-14, it was observed that there has been increasing investigation of different RS techniques since the year 2003 but SNRS, DLRS, and GARS did not come into existence till then. It was the year 2005 when the first work in the field of SNRS got published by the scientist J.Jung and thereafter research in this field is at an ever-growing pace. Despite the fact that CF is the most worked upon area since 2003, researchers have not been able to exhaustively solve the data sparsity and cold start problem. Hybrid RS is the second highest worked upon technique followed by CARS and CBS respectively. Furthermore, regardless of optimized results by GARS, it is still the novel technique that has not been investigated much by the researchers. First published work on GARS was in the year 2004 with no work in the subsequent year. However, from the year 2006, there has been constant swift in the investigation with the most work being done in the year 2014 and 2017 while the count still remains low due to its probabilistic nature and strenuous implementation. It is interesting to note that year 2011 shows a swift jump in the investigation of SNRS, GRS, and CARS while the same year marked a downfall in the investigation of other techniques compared to the previous year. According to our study, suppressing uncertainty and vagueness in user's behavior has given a boost to fuzzy based RS. It is also interesting to note that no evidence of research work on IRS was found in the year 2005 despite having significant works in previous years. Additionally, from Figure 14 it would be both strange and interesting to note that there was no work on DLRS till the year 2010 however within a short span of two years numerous approaches on DLRS have been proposed by scientists seeking to its advantages. Surprisingly, no technique shows the linear increase in the investigation but a fluctuating growth in the techniques of RS which may be due to the fluctuating demands of the market.

The details of various recommender system approach investigated, including evaluation metric used, dataset and period of discovery have been listed in Appendix 1. This analysis clearly shows the gradual increase in research work on RS over the years. Incorporating features mentioned in our study in the current RS will prove to be boon for many industries.

LIMITATIONS AND FUTURE WORK

The future investigation includes empowering the current techniques to improve the quality of recommendations. Some of the features that need to be worked upon are: (1) scalability and time complexity, (2) taking into consideration both user's long-term and short-term interest, (3) avoiding serendipity, (4) increasing data coverage, (5) avoiding overspecialization by adding some randomness in the system, (6) taking seasonal behaviour of consumer into consideration, (7) privacy and security of users, (8) developing a user-centric evaluation metric, (8) appropriate hybridization of existing techniques, (9) experimenting developed techniques on incremental real datasets ,and (10) building more optimised, flexible and accurate recommender system taking into consideration diversity and avoiding user boredom.

CONCLUSION

Evolution of web has led to information overload and thus RS proved to be a successful tool for filtering the information of use. In this paper, we highlighted some of the open research gaps, new trends and future directions with respect to various influential RS approaches expanding the horizons of research in this field. Additionally, analysis of the temporal distribution of recommender system techniques was conducted to study the growth of different recommender system techniques in recent years. With the growth of RS, evolved the evaluation metrics that are used to analyze the system developed. We discussed the advantages/disadvantages of various evaluation metrics. Currently, there is a need to create a user-centric evaluation metric. This survey was conducted with the intention of providing panorama through which educators, researchers, industry, and practitioners can quickly learn and understand the rationale behind recommendation enabling them to easily step into this field. Additionally, we tried discussing every aspect of the recommendation process including different recommendation techniques, datasets and popular evaluation metrics that needs to be considered for its development.

APPENDIX 1

References	Data Set	Evaluation Metrics
Wang et al. (2004)	Cosmetics Data set	Confidence, Lift
Massa and Avesani (2007)	Epinions	MAE, Coverage
Gao et al. (2008)	MovieLens	MAE
Bedi et al. (2009)	Jester Data Set	Recall, Precision, F-measure
Abbassi et al. (2009)	MovieLens	Discounted Cumulative Gain (DCG)
Bobadilla et al. (2011)	MovieLens, Film Affinity, Netflix	MAE, Coverage, Precision, Recall
Bellogin et al. (2012)	MovieLens	DCG, Precision, Coverage
Chen et al. (2013)	MovieLens	Precision, Recall
Lu et al. (2013)	MovieLens	Precision, Coverage
Yang et al. (2014)	Flixster, Epinions	MAE, RMSE, DCG
Lee and Lee (2015)	Last.fm	t-test
Wu et al. (2015)	MovieLens	MAE, Precision, Recall, F-measure
Yera et al. (2016)	MovieLens, MovieTweeting	MAE, F-measure
Koohi et al. (2016)	MovieLens	Recall, Precision

Livinus et al. (2016)	Amazon database	MAE, RMSE, Precision, Recall, Sensitivity, Specificity, F-measure
Hernando et al. (2016)	MovieLens, Netflix	MAE, Recall, Precision
Katarya and Verma (2017)	MovieLens	MAE, RMSE, t-value
Yera et al. (2017)	MovieLens, Jester	MAE, Recall, Precision, F-measure
Huynh et al. (2018)	MovieLens, Jester, MSWeb	ROC
Chen and Lee (2018)	Microsoft Academic Search	Recall
Nilashi et al. (2018)	MovieLens, Yahoo!Webscope R4	MAE, Precision, Recall
Katarya and Verma (2018)	Last.fm	Recall
Bansal and Baliyan (2019)	MovieLens	Recall, Precision, F-measure

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