Recommender Systems: An Overview, Research Trends, and Future Directions

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Recommender systems: an overview, research trends, and future directions

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Abstract: Recommender system (RS) has emerged as a major research interest that aims to help users to find items online by providing suggestions that closely match their interest. This paper provides a comprehensive study on the RS covering the different recommendation approaches, associated issues, and techniques used for information retrieval. Thanks to its widespread applications, it has induced research interest among a significant number of researchers around the globe. The main purpose of this paper is to spot the research trend in RS. More than 1,000 research papers, published by ACM, IEEE, Springer, and Elsevier since 2011 to the first quarter of 2017, have been considered. Several interesting findings have come out of this study, which will help the current and future RS researchers to assess and set their research roadmap. Furthermore, this paper also envisions the future of RS which may open up new research directions in this domain.

Keywords: recommender system; issues; challenges; literature review; filtering approach; filtering technique; information retrieval technique; machine learning; research trends; future direction.

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1 Introduction

"Which mobile phone should I buy?", "Which movie should I watch this weekend?", "Where should family and I go to spend the coming holidays?", "Which books should I carry during my long vacation?" – These are a few examples of very common indecision for which we often seek suggestions from our friends and known ones. Unfortunately, almost every one of us has experienced that those friendly suggestions, even with their best intention, are not really effective in many of the cases as others' taste does not necessarily mean to harmonise with that of ours. These suggestions may often also be biased. The other anomalous options we can endure, such as be a decision science expert and try out the complex theories, plunge into the internet and waste hours going through the confusing reviews and suggestions, hire an expert, go along the herd, or simply listen to our soul. The point is that it is very arduous to highlight a precise suggestion on the items on which we might be interested. It would be of great help if we would have a personal advisor who would assist us by suggesting the best option whenever we have to make a decision. Thankfully, we have one such in the form of a web application known as the recommender system (RS).

An RS is an intelligent computer-based technique that predicts on the basis of users' adoption and usage and helps them to pick items from a vast pool of online stuffs. Most internet users surely have happened upon an RS in some way. For instance, Facebook recommends us, prospective friends, YouTube recommends us the videos in accord, Glassdoor recommends us matching jobs, TripAdvisor recommends us suitable holiday destinations, Goodreads recommends us interesting books and so on. RSs have garnered phenomenal acceptance in the e-business scenario. E-Commerce portals (e.g., eBay, Amazon, etc.) are using RSs to entice customers by heaving with the products that customers should, presumably, going to like. This has helped them to attain a huge boost in sales. Not only the online business, but there are other applications also that take advantage of RSs, such as social networks, online news portals, entertainment sites, and other knowledge management applications. Actually, RSs have begotten a new dimension in the communication approach between users and online service providers. These days, many companies are adopting RS techniques as an added value to enrich their client services. Though, the implementation of an RS depends on the particular recommendation approach adopted by the application, the core working of RSs remain more or less the same for all applications. The focal objective of RSs is to aid users in their decision making in order to pick out an online item, by supporting with in-hand recommendations of high accuracy (Jannach et al., 2011). The potential of RS in different domains has attracted researchers to explore the possibilities exhaustively. Peoples from various disciplines such as data mining, information retrieval, knowledge discovery, artificial intelligence (AI), approximation theory, forecasting theory, information security and privacy, and business and marketing have contributed extensively with diverse research approaches (Jannach et al., 2011).

A lot of work has been done by the research community to enhance the applicability and performance of RSs over the last few years (Lu et al., 2015). New methodologies and algorithms were developed to address many of the technological challenges such as producing more accurate recommendation while reducing online computation time. Several recommendation algorithms have been proposed and successfully implemented in different domains. These algorithms mainly follow demographic filtering (DF), content-based filtering (CBF), collaborative filtering (CF) and hybrid approaches. Recently, RS has expanded its exploration and is using social networks and some contextual information to generate dynamic features in the recommendation. Furthermore, new approaches, either novel or amalgamations of existing methods, are continually being proposed (Jannach et al., 2011).

1.1 Contribution of this paper

This paper serves a fourfold purpose as mentioned below:

1 This paper presents an overview of RSs that cover the recommendation approaches, information retrieval techniques, and associated challenges and problems in RSs.

2 A brief survey of several survey papers on RS covering different aspects has been laid.

3 The primary aim of this paper is to study and map the research directions in the area of RS. As RS has attracted a lot of researchers from diverse fields of study, the amount of research publications on related topics is growing with a steep curve. Inspired by the considerable amount of attention the RS has purchased and motivated by the famous article on systematic reviews by Kitchenham (2004), we have endeavoured to track down the past and ongoing researches in the domain of RS. We have tried to hit upon some statistics that will stimulate and guide current and future researchers in the related field. Our effort attempts to answer the following questions:

   a What are the recommendation systems available in different applications?

   b Which issues and challenges have been focused related to different filtering approaches of RSs?

- c What are the potential areas that should be addressed?
- d How to find the popular research direction of RS on the basis of paper publications?
- e What are the most cited papers related to RS?

The research papers those are considered for this study are taken from ACM, IEEE, Springer, and Elsevier databases which are published in the time period from 2011 to early 2017.

4 A view on the future scope and trends of RS has been presented. The aim of this part is to provide the future researcher on RS a preliminary overview of various prospective research areas.

The highlights of this paper are presented pictorially in Figure 1.

Figure 1 Highlights of this paper (see online version for colours)

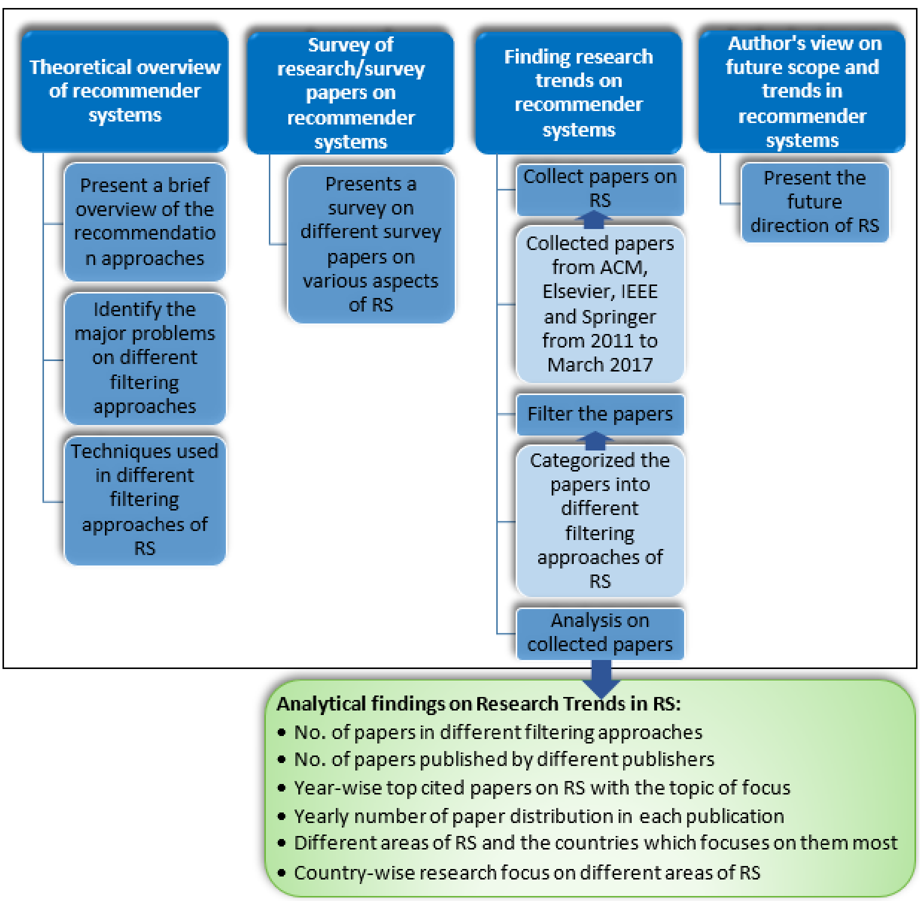


Table 1 A brief overview of the recommendation approaches

Recommendation	*Source of data*	*Extraction*	*Limitations*	*Research*
Content-based (CBRS)	Content related to product and user's information etc.	Document modelling, information filtering, and similarity metrics, etc.	Problems in content analysis, non-homogeneous items and no methods use in prediction of missing ratings, etc.	Siting et al. (2012), Protasiewicz et al. (2016), Park et al. (2012), Sikka et al. (2012), Sharif and Afzal (2015), Campos et al. (2014), Bobadilla et al. (2013), Nagarnaik and Thomas (2015), Bernardes et al. (2014), Xia et al. (2013), Chen et al. (2013), Song et al. (2012), Knees and Schedl (2013), Toch et al. (2012), Sachan and Richariya (2013), Sharma and Gera (2013), Borrís et al. (2014), Gavalas et al. (2013), Aldhahri et al. (2015), Yang et al. (2016), He et al. (2016) and Elahi et al. (2016)
Collaborative (CFRS)	Feedback on products from the user's side.	K-nearest neighbour, cosine and correlation-based similarity, etc.	Cold start problem, sparsity problem, synonym problem and false user's rating problem, etc.	Li (2011), Siting et al. (2012), Protasiewicz et al. (2016), Park et al. (2012), Sikka et al. (2012), Sharif and Afzal (2015), Campos et al. (2014), Bobadilla et al. (2013), Nagarnaik and Thomas (2015), Bernardes et al. (2014), Xia et al. (2013), Chen et al. (2013), Song et al. (2012), Knees and Schedl (2013), Toch et al. (2012), Sachan and Richariya (2013), Sharma and Gera (2013), Borrís et al. (2014), Gavalas et al. (2013), Aldhahri et al. (2015), Yang et al. (2016), He et al. (2016) and Elahi et al. (2016)
Demographic (DRS)	User's demographic information such as gender, age, date of birth, etc.	Clustering and locating group interest etc.	It totally depends on demographic information, which can be less accurate and static in nature etc.	Protasiewicz et al. (2016), Campos et al. (2014), Bobadilla et al. (2013), Xia et al. (2013), Sachan and Richariya (2013), Borrís et al. (2014) and Elahi et al. (2016)
Knowledge-based (KBRS)	User's information from social networks, data used for search, or query of the product, etc.	Machine learning and Decision rule etc.	More cost is required for knowledge acquisition; preferences are not always independent from each other, etc.	Zhang et al. (2011), Campos et al. (2014), Xia et al. (2013), Chen et al. (2013), Borrís et al. (2014), Gavalas et al. (2013), Hu et al. (2015) and Elahi et al. (2016)
Context-aware (CARS)	Data related to the different context of the user and product.	Text analysis, machine learning methods, classification, clustering, association rule, and neural network, etc.	Difficult to collect the desirable context for a recommendation because the user's context is dynamic in nature.	Protasiewicz et al. (2016), Verbert et al. (2012), Campos et al. (2014), Dejo et al. (2015), Xia et al. (2013), Borrís et al. (2014), Gavalas et al. (2013), Hu et al. (2015) and He et al. (2016)
Hybrid (HRS)	Any source that is mentioned in this table.	Any extraction method that is used in this table.	Diversity, novelty and serendipity of recommendation.	Protasiewicz et al. (2016), Sharif and Afzal (2015), Campos et al. (2014), Bobadilla et al. (2013), Nagarnaik and Thomas (2015), Chen et al. (2013), Song et al. (2012), Sharma and Gera (2013), Gavalas et al. (2013), Aldhahri et al. (2015), He et al. (2016) and Elahi et al. (2016)

1.2 The USP of this paper

A lot of survey works on RS, as recorded in Table 1, are available in the literature. But all of them focuses on the different theoretical aspects and applications of RS. We endeavoured to present a survey which primarily focused on tracking the research trends in the area of RS by following the method of the systematic survey (Kitchenham, 2004). As per the best of our knowledge, our effort is the first ever one of this kind in the area of RS.

1.3 Organisation of this paper

The rest of this paper has been organised as follows. Section 2 discusses the history and background of RSs. Section 3 describes the different approaches used in RS. Section 4 briefs the information retrieval techniques used in RS. In Section 5, the issues in RS are discussed. Some of the notable survey papers on RS are briefed in Section 6. Section 7 considers the paper collection and filtering approaches used in our research. It also discusses the findings with some purposeful graphs. Section 8 portrays a foresight on the traits and applications of future RSs as well the future research directions. And finally, Section 9 presents a brief discussion on the findings and concludes the paper.

2 History and background of RSs

Though Graundy (Rich, 1979), a computerised librarian, may be considered as an early step towards automatic RS (Ekstrand et al., 2011), the idea of accruing opinion of millions of online users in order to find more suitable and appealing contents have emerged in the early '90s. Tapestry (Goldberg et al., 1992), a manual CF system, allowed users to query for items in an online information domain. GroupLens (Resnick et al., 1994) has used a similar technique to identify the particular user's interest by using Usenet articles and based on the user's action to provide a personalised recommendation.

In the late '90s, the RSs started to capture the attention of the researchers from the domain of human-computer interactions, machine learning and information retrieval, and other allied disciplines. As a result, many RSs [such as Ringo (Shardanand and Maes, 1995) for music, the bell core video recommender (Herlocker et al., 2000) for movies, and Jester (Goldberg et al., 2001) for jokes] for different application domains have been developed. During the same period, the RS had been increasingly utilised in marketing to enhance sales, and customer experiences (Ansari et al., 2000) and many commercial applications of RSs were surfaced in the online realm (Linden et al., 2003). Gradually, recommendation approaches moved beyond the CF and many of the RS researchers' focus of interest shifted towards the content-based recommendation (CBR) approaches based on information retrieval, Bayesian inference, and case-based reasoning methods (Schafer et al., 2001; Bridge et al., 2005; Smyth, 2007). In 2006, hybrid RSs (Burke, 2002), attracted much attention and Netflix launched the Netflix prize to improve the aptness of movie recommendations.

Nowadays social networking sites (such as Facebook, Twitter, etc.) have emerged as a substantial platform for applying RSs. These popular sites are considered to be the major source of information about people and hence becoming a great option to leverage novel and innovative approaches for the recommendation, leaving behind the old methods, to increase the accuracy (Bernardes et al., 2014). The contextual information such as time, place, the emotion of people and groups in these social networking sites opens up a new avenue of recommendation known as contextual RS. It also provides a good prospect to bring a dynamic essence in the recommendation (Dejo et al., 2015). Seasonal marketing and conference recommendation (Zhang et al., 2016) are also emerging as considerable application areas in the context-aware recommendation.

3 Different recommendation approaches

Several recommendation approaches have been proposed and adopted in different applications. In this section, we present a brief overview of the popular recommendation/filtering approaches in RSs. Table 1 summarises these approaches along with the source of input data, the extraction method used, the limitations of each approach, and the research works emphasising the particular approach while Table 2 lists the popular application domains of RS with their filtering techniques and related research works.

3.1 Content-based recommender system (CBRS)

CBRS uses CBF to recommend items by matching user profile and item description. The user profile may include his previous search or purchase history (Pazzani and Billsus, 2007). The system learns to recommend items that are similar to the ones that the user liked in the past. The similarity of items is calculated based on the features associated with the compared items. For example, if a user has positively rated a movie that belongs to the comedy genre, then the system can learn to recommend other movies of this genre. To get an overview of CBRS, Lops et al. (2010) may be referred.

3.2 Collaborative filtering recommender system (CFRS)

This is the most recognised and widely implemented RS (Burke, 2002; Singh et al., 2019d). CFRS follows the philosophy of “a man is known by his company he keeps.” That means if CFRS believes that if two or more user’s interests matched in the past, then it is likely that in future also their interests should match. For example, if the purchase histories of user1 and user2 strongly overlap then it is high on the cards that if user1 buys a product, then user2 will also buy the same or similar product. CF approaches to keep track of the user’s past reviews and ratings on items to recommend similar items in the future. Even if the user did not deal with a particular item, it would be recommended to him if his peers have used the same (Deshpande and Karypis, 2004). It is obvious that to achieve reasonable recommendation accuracy a large number of user groups are required to be considered. Trust is an important factor for reliable recommendation. Moghaddam et al. (2014) has considered a trust-based CF approach to present a temporal-trust-based method to measure trust value. The methodologies and techniques of CFRS in details can be found in Ekstrand et al. (2011). There are various categories of CF such as (Su and Khoshgoftaar, 2009):

1 *Memory-based collaborative recommender system (CRS):* similarity measure and the prediction computation are the two main steps used in the memory-based CRS, which is further categorised into two parts based on their similarity computation method as follows (Badrul et al., 2001; Singh et al., 2019b):

   a *Item-based CRS:* similarity computation is performed on a set of items (Singh et al., 2019b).

   b *User-based CRS:* similarity computation is performed based on the similarity values of users (Singh et al., 2019c, 2019f, 2019e).

2 *Model-based CRS:* in model-based CRS (Gong et al., 2009), different machine learning algorithms such as Bayesian network, clustering, Markov decision process, sparse factor analysis, dimensionality reduction techniques, and rule-based approaches, etc., are used to build a model for the recommendation.

3.3 Demographic recommendation system (DRS)

DRS works based on the users' demographic profile such as age, sex, education, occupation, locality, etc. It generally uses clustering techniques to categorise target users according to demographic information. But in this RS if the demographic attributes remain unchanged, the user will receive the recommendation for the same set of items. Thus, they might miss some new and worthwhile recommendation. Demographic information about a user can improve the accuracy of RS (Pazzani, 1999).

3.4 Hybrid recommender system (HRS)

As the name suggests, hybrid RS is the product of the combination of multiple filtering approaches. The most popular pairing HRS is that of CBS and CFRS. The purpose of combining different filtering approaches is to improve the accuracy of recommendations (Burke, 2007) while eliminating the limitations of the individual filtering approaches.

3.5 Knowledge-based recommender system (KBRS)

To recommend the items such as flat, bike, TV, etc., which are less frequently purchased by a user, sufficient information on the basis of which recommendation is made may not be available or relevant (even if available) (Jannach et al., 2011). For that, some additional information (e.g., the user's social network activity) is required. Knowledge-based RSs provide a recommendation based on additional knowledge model related to the relationship between the present user and items. Case-based reasoning technique is a common feature of KBRSs that divides the user's need into multiple cases, depending on various criteria and provide recommendations that closely matches to user's likely preference (Bridge et al., 2005). Another type of KBRS, known as constraint-based RS that works as per the user's preference and recommends items that match the preference (Felfernig and Burke, 2008). If no such item is available, then a set of alternative items that are close to the preferred item is recommended. Semantic web technology can help to establish a diversified knowledge base of the users and the items. It utilises ontologies, a formal knowledge representation the method that is used to express the domain knowledge of users and items (Middleton et al., 2009). The similarity between items can be calculated based on domain ontology (Cantador et al., 2008). Metadata of a user profile and item description are used to establish a proper matching for the recommendation. Many problems (discussed in Section 5) of common RSs are eliminated by using semantic-based RS. More details of the semantic-based RS can be found in the article (Peis et al., 2008). As an example, Wang et al. (2015b) may be referred to, where the authors proposed and evaluated the preference of a semantic-based friend RS for the social network. Though KBRS is capable of providing the required information that cannot be achieved through the conventional approaches, the knowledge modelling and handling techniques in KBRSs are comparatively expensive in nature (Pelánek, 2018).

3.6 Context-aware recommender system (CARS)

If the target user's contextual information is available, we can make the RSs ubiquitous (Jannach et al., 2011). Various attributes like time, location, companion, mood, etc., can define a context. The difference between contextual information and demographic information is that demographic properties of a user generally remain the same for a longer period, whereas contextual information changes when the surroundings of the user change. Hence the mobile applications play a significant role in CARS. CARS plays an important role, especially in personalised and direct online marketing. The more relatable and specific recommendation can be provided by capturing the emotional context of the user (Jannach et al., 2011). An example of using emotional context for recommendation can be found in González et al. (2007). To capture the emotional context, a hefty amount of data managed which leads to various challenges (Lakshmi and Lakshmi, 2014). Sarwat et al. (2015) have proposed CARS that can be built into a database system. A context-aware online learning environment has been presented in Mayeku et al. (2015). An effective way to extract the worthwhile contexts from user's comments available on YouTube is depicted in Orellana-Rodriguez et al. (2013, 2015). An explanatory piece on CARS can be found in Adomavicius and Tuzhilin (2010).

Table 2 Popular application domains of RSs with their filtering techniques and related research works

Application domain	*Filtering approaches used*	*Related research papers*
E-government	Knowledge-based	Meo et al. (2008), Terán and Meier (2010), Esteban et al. (2014) and Cornelis et al. (2007)
	Collaborative	Guo and Lu (2007)
	Collaborative, hybrid, knowledge-based	Wu et al. (2015) and Lu et al. (2010)
E-library and e-learning	Content-based, collaborative, hybrid	Balabanović and Shoham (1997) and Renda and Straccia (2005)
	Hybrid, knowledge-based	Porcel et al. (2009b, 2009a), Porcel and Herrera-Viedma (2010), Serrano-Guerrero et al. (2011) and Cobos et al. (2013)
	Knowledge-based, content-based	Zaíane (2002), Chen et al. (2004), Chen and Duh (2008), Capuano et al. (2014), Farzan and Brusilovsky (2006), Santos et al. (2014), Lu (2004) and Biletskiy et al. (2009)

Table 2 Popular application domains of RSs with their filtering techniques and related research works (continued)

Application domain	*Filtering approaches used*	*Related research papers*
E-tourism	Knowledge-based	Burke et al. (1996), Fesenmaier et al. (2003) and García-Crespo et al. (2011)
	Knowledge-based, collaborative, context-aware, hybrid	Avesani et al. (2005), Burke (2002), Martínez et al. (2009), Ruotsalo et al. (2013), García-Crespo et al. (2009), Console et al. (2003) and Moreno et al. (2013)
	Content-based, collaborative, hybrid, demographic	Schiaffino and Amandi (2009), Luz et al. (2013) and Baraglia et al. (2012)
	Context-aware	Tung and Soo (2004), Pashtan et al. (2003), Rikitianskii et al. (2014) and Xie et al. (2013)
	Collaborative, context-aware	Xie et al. (2013)
E-resource	Content-based	Jinni (2017), RottenTomatoes (2017), IMDb (2017), Asnicar and Tasso (1997), ACRnews (2017), Chesnevar and Maguitman (2004) and Park (2013)
	Collaborative	Ali and van Stam (2004), Goldberg et al. (2001), Resnick et al. (1994), Konstan et al. (1997), FoxTrit (2017), Miller et al. (2004), Hauver and French (2001), Marcel et al. (2003), Lee et al. (2010), TASTEKiD (2017), nanoCROWD (2017) and Movielens (2017)
	Context-aware, collaborative	Braunhofer et al. (2013), Baltrunas et al. (2012), Levandoski et al. (2012), Natarajan et al. (2013) and Oh et al. (2014)
	Collaborative, knowledge-based	Zhang et al. (2011), Hayes and Cunningham (2001), Sánchez et al. (2011) and Boutet et al. (2013)
	Content-based, collaborative, hybrid	Smyth and Cotter (2000), Blanco-Fernández et al. (2006), Salter and Antonopoulos (2006), Melville et al. (2002), Domingues et al. (2013), Christou et al. (2016), Parra et al. (2014) and Amolochitis et al. (2014)
	Knowledge-based, content-based	Jäschke et al. (2007), Hotho et al. (2006), Celma and Serra (2008), Bjelica (2010), Moukas and Maes (1998), Billsus and Pazzani (2000), Nguyen et al. (2014), Martín-Vicente et al. (2012) and Zhang et al. (2012a)
E-commerce	Knowledge-based, demographic	Garfinkel et al. (2006), Mccarthy et al. (2004), Cao and Li (2007), Hu et al. (2012), Zhao et al. (2016) and Zhao et al. (2014)
	Knowledge-based, content-based	Burke (1999), Nanopoulos et al. (2010), Zhang et al. (2013) and Yin et al. (2014)
	Collaborative, hybrid	Linden et al. (2003), Pratikshashiv (2015), Lawrence et al. (2001), Chen and Pu (2012), Walter et al. (2012) and Liu and Karger (2015)

4 Information retrieval techniques in RSs

Numerous sources of information have crammed the digital world with unbounded data. The scenario has been exaggerated by the interactive participation of people. To deliver an effective and fruitful recommendation, the RS needs to study all possible zones of dealings to extract and analyse informative data to understand people's preferences and tastes. To carry out this job every RS employs some information retrieval techniques. Some of the most popular information retrieval techniques used in RSs are mentioned below.

4.1 Machine learning

Machine learning provides an entity (machine) the ability to learn, artificially, without programming explicitly. It applies different algorithms like logistic regression, decision tree, association rule learning, cluster, Bayesian networks and support vector machine, etc.

4.2 Logistic regression

Logistic regression is used for the prediction of discrete variables by using continuous and discrete data (Wang, 2011). To consider a collaborative tag RS, Montanes et al. (2009) have utilised this technique to rank the meaningful tags in social networks. Logistic regression is also used in determining the trustworthiness of a user by identifying the probable attacks in CFRS. For instance, Zheng et al. (2011) have used this technique to suggest a robust CF algorithm that detects malicious attacks in RS by calculating the trustworthiness of users.

4.3 Decision tree

The decision tree is a powerful technique that helps in choosing an option among multiple alternatives. In RS, it is used to calculate and predict the missing preferences of users. Yu (2012) has used this technique in tackling the cold-start problem to provide a high-quality service recommendation for new items.

4.4 Association rule learning

Association rule learning is used to extract the frequent patterns, associations, correlations or causal structures from users and items dataset for recommendations. Tewari et al. (2014) have applied association rule mining in a combination of CBF and CF to predict the buyer's interest for the book recommendation. In another work Tewari and Priyanka (2014) have also used association rule mining with classification and CF to recommend books to the students based on the given price range and preferred publishers. Association rule is used in Jomsri (2014) to model a book RS for digital libraries.

4.5 Cluster analysis

In RS, to make a group, among a large set of objects, based on similarity, structures, and patterns, cluster analysis (i.e., unsupervised learning technique) is used. Habibi and Popescu-Belis (2015) have mentioned the problem of keyword extraction from documents and provided a solution for document recommendation in conversations by applying cluster analysis based on keyword similarity. West et al. (2016) have presented a simple citation-based method for recommending articles by clustering based on the user's recent history and searching patterns.

4.6 Bayesian network

A Bayesian network classifier (i.e., a probabilistic model) is applied to solve classification problems in huge networks like social networks. To solve the user's cold start problem and improve accuracy in the recommendation, Wang et al. (2015a) proposed a trust-based probabilistic recommendation model for social networks.

4.7 SVM

Support vector machine (i.e., supervised learning) is used with an associated learning algorithm for analysing data using classification (linear and nonlinear) and regression analysis. Zhang and Zhou (2014) have used this technique along with Hilbert-Huang transform to detect profile injection attacks in CFRS.

4.8 LDA

Extracting a common topic from various documents is called topic modelling. A topic is identified with the help of a different combination of words in a document. LDA (a probabilistic model of a corpus) used for topic modelling in RSs. To overcome the sparsity problem in rating dataset, Wilson et al. (2014) have proposed an improved CF algorithm for recommending, using the topic modelling on a textual description of items. TV users face difficulties in finding. To help TV viewers in finding the favourite TV program from countless numbers of TV programs (through various channels), Pyo et al. (2015) have introduced an LDA-based unified topic model for TV program recommendation.

4.9 TF-IDF

TF-IDF (2017) is used to extract the important words from documents for identifying the topic. TF-IDF is used in Oku et al. (2014) for document retrieval to recommend tourist spots. TF-IDF is used in Kywe et al. (2012) to find similar user and tweets in hashtag recommendation for Twitter users.

4.10 Deep learning

Deep learning plays a major role in extracting hidden patterns from data and has opened up a new area in data mining research (Hinton and Osindero, 2006). It can be used in the building of effective and dynamic behaviour modelling in RSs. We can gather intrinsic details about the user by understanding the approaches of supervised and unsupervised learning in the deep neural network (Zheng, 2016). van den Oord et al. (2013) have proposed ‘deep content-based music recommendation’ to minimise the problems in music RS by predicting the latent factors from music. Using the deep generation model and deep ranking model, Covington et al. (2016) have presented a deep neural network for recommendations on YouTube, one of the most popular RS for videos. The deep generation model is used to take input from the user’s side, and the deep learning model is used to rank the recommended videos. Elkahky et al. (2015) have illustrated a content-based RS with a deep learning approach to maximise the similarity between users and their preferred items in latent space. They also extended their models in different domains to extract more features related to users and items.

5 Problems associated with RSs

Most of the conventional RSs, discussed in the previous section, suffer from some serious drawbacks which restrain the effectiveness of the RSs. In this section, some of the major issues are discussed briefly. Table 3 summarises these issues and the research papers where these problems are attempted to be addressed. The table also mentions the filtering approach which is affected by these problems particularly.

5.1 Limited content analysis

In CBRS, the accuracy of recommendation depends on the extent of user input provided. If the RS does not contain sufficient information about a user, the performance of the recommendation will be low. No CBR system can provide suitable suggestions if the analysed content does not contain enough information to discriminate items the user likes from items the user does not like (Lops et al., 2011). This problem is known as limited content analysis problem. To make a precise recommendation, the complete domain information is required. For example, an RS for movies needs to have all the information related to a particular movie (e.g., genre, actors, directors, etc.). But gathering all the information related to a particular domain is very difficult, especially for multimedia items like images, audio and video streams, etc. Hence, this problem is also referred as a domain dependency problem. This problem can be resolved by adopting KBRS.

5.2 Over-specialisation

The aim of a RS is to help users explore new products. Diversity is an important feature of a good RS. Unfortunately, some recommendation algorithms may do exactly the opposite. They tend to recommend the popular and highly rated items which are liked by a particular user. This leads to lower accuracy as CBRS does not recommend items from a non-homogenous set of items (Thorat et al., 2015). To overcome this problem, there is a need to develop new hybrid approaches which will enhance the efficiency of the recommendation process. The learning methods applied to CBF try to find the most relevant documents based on the user’s behaviour in the past. Such an approach, however, restricts the user to documents, similar to those already seen. This is known as the over-specialisation problem.

5.3 Cold start

When a new item or a new user is introduced to an RS, the system will not have any past records (ratings, preferences, search history, etc.) on the basis of which recommendation should be made (Lakshmi and Lakshmi, 2014; Su and Khoshgoftaar, 2009). This is known as the cold start problem. It is also termed as the new user problem or new item problem. A solution to this problem includes exploiting the demographic information of the user obtained from the user's profile. This solution is insufficient and not completely correct as users with the same demographic features may show varying interests towards a particular item.

5.4 Sparsity

In practice, the RSs work with very large datasets. Hence, the user-item matrix used for CF is extremely sparse, which adversely affects the performances of the predictions or recommendations of the CF systems. It also takes place when a user, having used some particular product, did not bother to rate it. In other cases, users do not rate items that are not known to them (Lakshmi and Lakshmi, 2014; Su and Khoshgoftaar, 2009). To overcome this problem, RS employs an approach called the clustering method. Clustering method refines the data according to the preference of the user, and by doing so, it makes it easy for recommending items. Unfortunately, there are certain issues that are yet to be resolved in the case of multi-level clustering.

5.5 Scalability

As the RSs work on large datasets, the complexity of the RSs increases in case of a huge number of users and millions of distinct items set. Many systems need to react immediately to online requirements and make recommendations for all users based on their purchases and rating history, which demands high scalability items (Thorat et al., 2015).

5.6 Synonymy

Synonymy refers to the problem of multiple words having similar meanings (Meymandpour and Davis, 2015). Most of the RSs are unable to find the same or similar items with different names (synonyms). On account of this incapability, some associated problems emerge. For example, 'children movie' and 'children film' basically denote the same items, but memory-based CF systems would find no match between them to compute similarity (Amazon.in, 2017a, 2017b).

5.7 Abbreviation

If the RS is not familiar with the abbreviations that the users often use during online interactions, it will not be able to recognise the item that the user is looking for. This generates an erroneous recommendation. The solution is to categorise the abbreviated words with their full forms and put both the names on the same list.

5.8 Long tail

If an item initially is not well-rated or not rated at all in an RS which follow a top-N recommendation, then over the time it will perish from the recommendation catalogue. Diversity is closely related to this problem. It emphasises the need for recommending diverse items to the users and how different the items are with respect to each other. But RSs fail to cooperate with this aspect which leads to the long tail problem (Shi, 2013). A user will miss recommendations for many necessary items just because he did not rate those items or did not have any access to them. This generally leads to the long tail problem (LT). It occurs when many items remain unrated or low rated.

Table 3 Major problems with recommendation approaches, the affected filtering approaches, and the research papers in which they are addressed

	Filtering approach that suffers						
Problems in	*Content-based*	*Collaborative*	*Demographic*	*Hybrid*	*Knowledge-based*	*Context-aware*	*Research works*
Contextual data requirement						√	Feng and Tran (2019) and Singh et al. (2019a)
Extra knowledge modelling requirement					√		Berghofer et al. (2003) and Zhang et al. (2013)
Long tail		√		√			Park (2013), Hamedani and Kaedi (2019) and Millecamp et al. (2019)
Black box		√		√			
Abbreviation	√	√	√	√			Shen et al. (2001) and Chatti et al. (2013)
Synonymy	√	√	√	√			
Scalability		√		√	√	√	Varudkar et al. (2019) and Koshti et al. (2019)
Sparsity		√					Ahmadian et al. (2019) and Sahu and Dwivedi (2019)
Cold start		√					Revathy and Pillai (2019) and Zhu et al. (2019)
Over specialisation	√		√				Adamopoulos and Tuzhilin (2014) and Cazella and Alvares (2005)
Limited content analysis	√		√				Zhang et al. (2012b), Chidlovskii et al. (2001) and Pereira and Varma (2019)

5.9 Black-box problem

The efficiency of the RS is enhanced with the increase in the transparency of recommendation. The satisfaction of the user in the recommendation is entangled with the trust that the user places on the objectives of recommendation. The black box problem occurs in RSs when the system is opaque towards the end user, causing decreased levels of confidence in the system (Ramaswamy, 2015; Lee et al., 2014). The potential of the recommendation is thus diminished by the black box problems that induce a lack of confidence in the minds of the users which lead to an unsuccessful attempt of recommendation (Asmus et al., 2014). This problem is overcome by providing information to the user regarding the basis on which the recommendations are made to them such as the interest patterns of other users, the profile generated by their own interest, etc. This motivates the users to go for the item as they are influenced to some extent by choice of their fellow users who also went for the same item. By providing the transparent reasons to the user, such as ratings on an item provided by similar users, the users are motivated to place their trust and confidence in the recommendation as well as the recommended items (Seroussi, 2009). For example, Netflix performs movie recommendations to its users on the basis of their huge background algorithms, but they make sure that it is always looking appealing to the user by revealing the basis of their recommendations.

6 Notable survey papers on various aspects of RSs

The exponential growth of the internet has made it difficult to find relevant information within a reasonable time limit. Social tagging systems have appeared as one of the solutions to tackle this problem. Lee and Yong (2007) have offered a summarised outlook on the recent progress on tag-aware RSs, their algorithms and future challenges such as polysemy and synonymy problems.

The cross-domain recommendation is an emerging research theme that aims to minimise the sparsity problem in RSs. Li (2011) has presented a brief survey of the pilot studies on CF domains and also summarised the related works on cross-domain CF.

Siting et al. (2012) have proposed a solution to eradicate the information overload problem in job recommendation. Protasiewicz et al. (2016) have introduced an architecture of a content-based RS for reviewers to evaluate research proposals or articles.

In the survey work by Park et al. (2012) that closely matches that of ours, 210 research papers published in the period between 2001 and 2010 on RSs have been picked for study. The authors have elaborated the future research directions in the field of the RS and mention the various data mining techniques such as heuristic method, regression, neural network, link analysis, K-NN, decision tree, clustering, association rule, etc., and application domains (e.g., recommending books, documents, images, movies, music, online products, TV programs, and others) of RSs.

A personalised e-learning system intends to let up the difficulties often faced by online learners while searching suitable materials related to their interest from the sea of online resources. A literature review on e-learning RSs based on content-based, CF and web mining techniques have been presented in Sikka et al. (2012) which might be handy for the future e-learning researchers' community.

Contextual information has been playing an important role in the learning-based RS. Verbert et al. (2012) have proposed a framework that can be used in a variety of technology-enhanced learning applications. The context-awareness in the RSs has been derived by utilising common contextual dimensions like time, location, group, etc.

Campos et al. (2014) have presented a comprehensive survey and analysis of the state-of-the-art on time-aware RSs. They also proposed a general guideline to evaluate the time-aware RSs. Dejo et al. (2015) have discussed a survey on context-aware RSs while elaborating its background and open issues like privacy and security.

Bobadilla et al. (2013) have portrayed an overview of RS as well as the cold start problem in CF method. They have explained the various quality measures and evaluation metrics of RSs. Several filtering approaches are used in RSs. Nagarnaik and Thomas (2015) have reported the filtering approaches used in RSs and also proposed a novel method for an efficient web page recommendation based on hybrid CF, i.e., using CF and CHARM algorithm.

To improve the pertinence, the need for social networks in RS has been examined and compared the different types of social network information to evaluate RSs (Chen et al., 2013). Researchers have explored social network analysis for association rules, CF and social recommendation which provide a new way to implement RS (Bernardes et al., 2014). Some performance metrics are also explained in this paper for the evaluation of RSs.

Mobile devices have become the ideal agent of RSs, but scanty of storage in mobile devices constrains the storing of enough user data that is required for the accurate recommendation. Researchers are coming out with various approaches to tackle this. Three smart communities such as mobile social learning, mobile event guide and context-aware services for a recommendation has been elaborated, and the authors have also highlighted the open issues on contextual information and social properties with respect to the recommendation to improve the relevance and accuracy (Xia et al., 2013).

RS for music is a part of multimedia information retrieval that has been gaining a fair research interest in recent years. A significant number of research papers have been published in the field of music RSs. The three main components (user modelling, item profiling, and match algorithms) in music RSs are discussed, and the authors have presented a survey of state-of-the-art approaches in music recommendation while focusing mainly on two popular algorithms: CF and CBF (Song et al., 2012). Song et al. (2012) have also proposed a motivational-based model related to empirical studies of human behaviour, sports education and music psychology. Knees and Schedl (2013) have provided an overview of music RS based on contextual music-data and also pointed out the characteristics of the presently available context-based measures with their drawbacks. They also reviewed the main three types of context-based similarity approaches: text-retrieval-based approaches (based on web-texts, tags, or lyrics), co-occurrence-based approaches (based on playlists, page count, microblogs, or peer-to-peer networks), and approaches based on user ratings or listening habits.

The extensive use of social networks and similar applications has brought on new privacy concerns in the digital world. Information about the users' physical location, their searching, usage, and viewing behaviour and history, and their online comments and review must be secure. A survey on user's attitudes related to privacy in RS has been presented to design personalised RSs (Toch et al., 2012).

CF has been the most used filtering approach in RS. Many researchers have used this approach for research. Also, substantial work has been done in trying to minimise the challenges of using CF in RS. The research article describes the types of filtering used in recommendation such as DF, CBF, and CF with a special mention on the challenges of CF (e.g., cold start problem, data sparsity, scalability, accuracy, etc.) (Sachan and Richariya, 2013). Another research paper also discusses the three major categories of recommendation approaches such as CF, CBR and hybrid recommendations (Sharma and Gera, 2013). The challenges of RSs, e.g., sparsity problem, cold start problem, scalability, and over-specialisation, are also discussed in this paper. The mass adoption of the mobile Internet has fuelled the utilisation of CF in the prediction of users' interest. Yang et al. (2016) have demonstrated a framework based on users' activity and different types of data generated by them, including rating information. The proposed framework mitigates the sparsity problem to some extent. A comprehensive study of different evaluation methods and matrices that have been employed by CF in RS (Elahi et al., 2016). The authors also analysed the surveyed approaches used in RSs.

Tourism RSs provide personalised and relevant suggestions for the tourists, related to the places they are visiting or planning to visit. These RSs not only deal with the textual information but also handle images and interactive maps. Along with surveying some research articles, the authors explained the application of the knowledge-based features in tourism RS (Borrís et al., 2014). Many researchers have tried different approaches (e.g., CBF, CF, DF) for tourism RS. But since all of these filtering approaches tend to suffer from some drawbacks, some RSs have combined two or more different approaches so as to overcome these drawbacks. Hence, researchers proposed hybrid recommender approaches that also include some contextual and personalised information collected through social networks and other means. Gavalas et al. (2013) have presented a classification of mobile tourism RSs and highlighted some research challenges in tourism RSs. Hu et al. (2015) also proposed a general framework based on taxi GPS trajectory for improving accuracy in tourism RS.

Aldhahri et al. (2015) have presented a survey on the RSs for crowdsourcing and other online systems which recommend potential service providers that closely matches with the requisite service. They highlighted the drawbacks in existing crowdsourcing RSs.

Many years of extensive research on RSs has led to evolving of several algorithms in diverse application domains. As an example, He et al. (2016) came up with an interactive visualisation framework of RSs based on different recommendation approaches to support human-recommender interaction while scrutinising the existing interactive RSs. They also suggested future research opportunities in the specified field.

7 Research trends in RSs

7.1 Paper collection

In order to build the target database, the research papers, including journal articles and conference proceedings were collected from four major electronic databases, namely: ACM Digital Library, IEEE Explore, Springer, and Science Direct (Elsevier). These databases were selected particularly because they generally are regarded as authentic and esteemed sources of quality research journals and conference proceedings in the area of computers and its allied fields (Ghanam et al., 2012). We believe that the quantity of a representative sample of the relevant pieces of literature required for this research is sufficiently available in these databases combined.

Since we settled in to capture the recent research direction in RS, our research focuses on the latest publications. Hence papers published from 2011 to 2017 (March) have been taken into consideration only. To find the desired papers from these databases, we executed the following queries in Google Scholar.

a [RSs OR (issue OR issues OR challenge OR challenges OR problem OR problems)].

b [Recommendation systems OR (issue OR issues OR challenge OR challenges OR problem OR problems)].

For filtering the retrieved papers, the following adjustments were followed.

a The desired query entered into the Google Scholar search engine.

b The date range had set to: 2011–2017.

c The 'published in' field in the advanced search box had set to: IEEE OR Elsevier OR ACM OR Springer.

7.2 Observations

We have considered 1,005 research papers that were published during the time period from January 2011 to March 2017. Those papers are studied and categorised on the basis of the main focus of the considered paper as shown in different figures. The computing for the experimental procedures and the graph plotting has been done using R studio, tableau, and MATLAB. Figure 2 shows the share (out of 1,005) of the paper published in each category of RSs. The categorisation of the collected papers has been done on the basis of keywords and abstract of each paper. Survey papers of RSs, papers related to database, algorithms, and performance of RSs, etc., have been included in the category of 'survey papers and others'. As mentioned above, we have collected papers that are published by ACM, IEEE, Springer, and Elsevier. Figure 3 shows that most of the papers (473) that we considered are from IEEE. One reason for that may be, compared to others, IEEE publishes more conference proceedings. We have tried to analyse the citations of the RS research papers to find out the research pattern on RS. Figure 4 shows the year-wise top cited papers on RS from each publication database also mentioning the main theme (area) of those top cited papers. For instance, in 2011 the most cited paper in RS is a survey paper, and that is published in Springer. Similarly, IEEE has the credit of publishing the most cited papers in 2013 and 2014 both, and the papers address the area of CF and KB respectively. The number of RS research papers published from each academic database in each year (from January 2011 to March 2017) is shown in Figure 5. We have tried to find out the country-wise research interest in RS. To shun the confusion, we have considered the country of only the first author of each paper. Figure 6 highlights the different areas of RS and the countries which focus (according to the number of publications) most of those areas. For example, research on CF has produced the highest number of papers, and most of their first authors belong to China. Figure 7 shows the country-wise research focus on different areas of RS. For example, the graph shows that China has published a maximum number of papers on RSs (based on collected papers) and most of them are focussed on CF.

Figure 2 Share of a number of research papers for different filtering approaches of RS (see online version for colours)

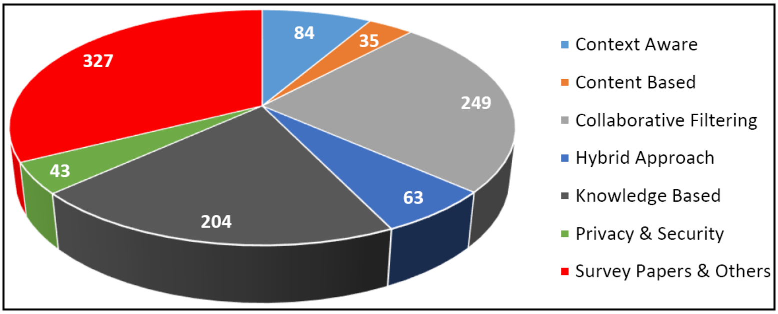


Figure 3 Share of a number of research papers published by different publishers (see online version for colours)

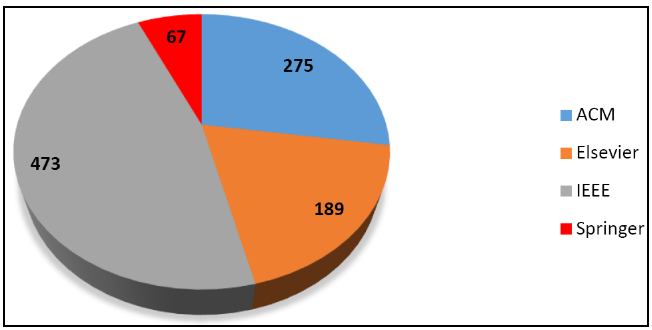


Figure 4 Year-wise top cited papers on RS with their themes (see online version for colours)

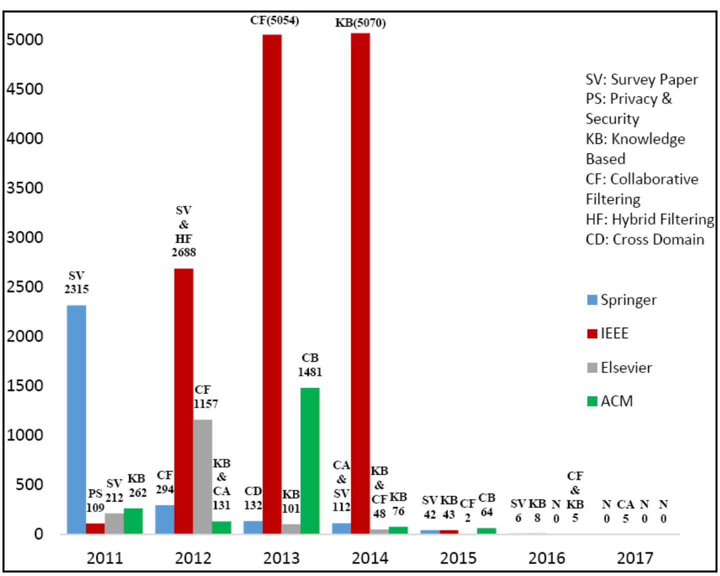


Figure 5 Yearly number of paper distribution in each publication (see online version for colours)

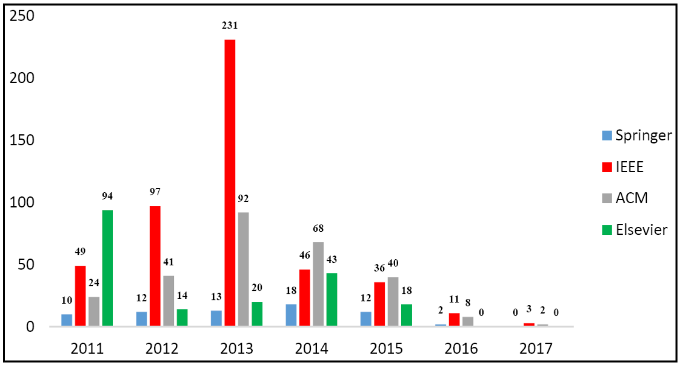


Figure 6 Different areas of RS and the countries which focus on the most (see online version for colours)

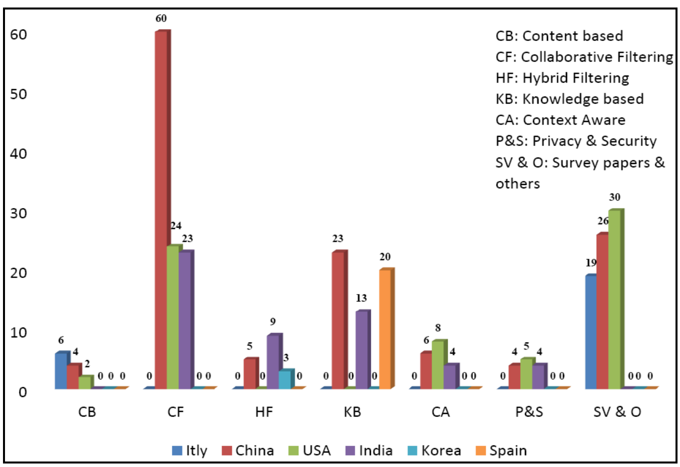
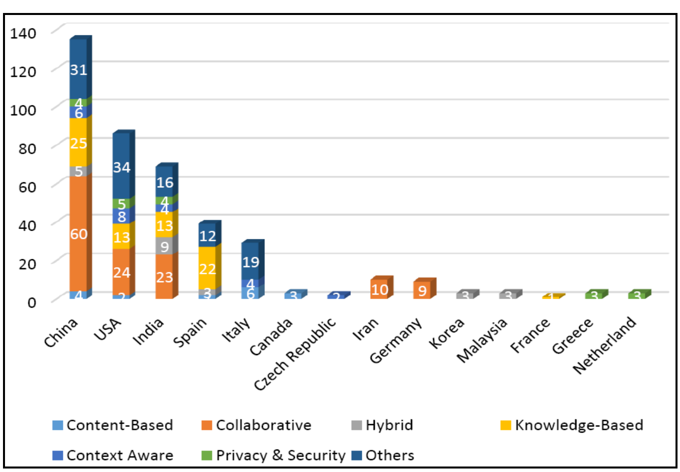


Figure 7 Country-wise research focus on different areas of RS (see online version for colours)



8 Future directions of RSs

To date almost all of the RSs have been designed for sellers, producers, and service providers, i.e., they are designed to attract potential customers. We believe that future RSs will not only be limited to business, but they will have a much greater impact on our daily life (Bourke, 2015). These systems will become truly ubiquitous and become an essential tool in every sphere of our life. The future RSs will not be bound merely to the applications for buying and selling products; rather it will become a sort of personal advisor which will assist in every sector of living by giving important suggestions and guidance (Narayanan and Cherukuri, 2016). The ideal RS should be like someone who knows us better than we know ourselves. They should sense our need and will suggest instinctively, even if we do not express explicitly. Few other fields like the internet of things (IoT) (Al-Fuqaha et al., 2015), internet of everything (IoE) (Yang et al., 2017; Miraz et al., 2015), AI, cognitive computing (Pramanik et al., 2018a), affective computing (cognitive science and psychology) (Tao and Tan, 2005), etc., will play a significant role in future RSs. They will be applied to a broader range of applications and also will be able to map user and products better by understanding better not only users but also the products. Future RSs will blur the demarcation between search and recommendations. In fact, RS will be an integral part of the future search engine which will be able to offer personalised search. It is very hard for the users to figure out the rationale and logic behind the recommendation they get (Herlocker et al., 2000). The RSs will be more open. It is especially important in the case of a merger of searching and recommending. If people understand the recommendation pattern, they will search more judiciously.

The RSs will be more intuitive and will continuously improve the quality of the recommendation by taking up user feedback loops from various sources. They will also be more flexible by supporting multi-criteria ratings. Future RSs will come up with innovative recommendation models using reinforcement learning or extensions of recurrent neural networks (RNN) (Liu and Singh, 2016) that will enable them to be accurately context, time, and mood-aware (Qian et al., 2019; Wu et al., 2016). They will be designed not only to recommend something but to understand when what to recommend and what not to recommend. Below some of the properties of future RSs and the application areas that will leverage the RSs are discussed.

8.1 Data-driven

The RSs will primarily be driven by IoT (Pramanik et al., 2018b), IoE and big data (Verma et al., 2015). The major differentiating point of future RSs will be the intelligent use of ubiquitous data. Data will be captured, assessed and analysed literally from anywhere and for anything (Pramanik and Choudhury, 2018). Though tackling the ever-increasing data will be a great challenge for the future RS designers because the current algorithms may not be straightforwardly scalable to cope up the unforeseen amount of data.

8.2 No cold start problem

Future RSs will be able to get rid of the ‘cold start problem’ by collecting suitable and implicit information from other online sources (Vairachilai et al., 2016). Social networks, IoE and every possible way of pervasive connectivity will be the main enabler for this.

8.3 More customer-centric

Existing RSs are typically seller-centric, i.e., users get recommendations of only those products which the sellers intend to sell (Fazeli et al., 2018). This restricts the buyers’ independent preferences. Future RSs should serve buyers better by being more buyer-centric. Sophisticated data analytics tools will empower retailers by enabling them to analyse and find a valuable pattern in people’s online purchasing habits. They can capture the obvious tendency of the buyers for the products they are initially interested in and eventually what they purchase. They will also use the information of which products buyers put in their cart and among them which are eventually bought and which are not (Krzanich, 2017). Recommending based on these observations will offer buyers an optimised shopping experience. By means of IoT, the manufacturer or the service providers can obtain the usage metrics of the products or services for each user and attune their products or services and pricing strategies accordingly (Vázquez, 2013). A left-hander should get product recommendations that are suitable for him.

8.4 More personalised recommendation

Recommendations will be more personal and individualised by analysing personal habits and behaviours. RSs will use virtual reality that will engage users in more personalised shopping. With the help of virtual reality and the power of data, future RSs will be smarter, responsive, connected and secure (Krzanich, 2017). They will be able to recommend more personalised entertainments. For example, today’s smart TVs tracks viewing information such as when, how often and what we watch. Analysing this information can suggest viewers’ behaviour patterns, hobby, entertainment and leisure preferences, their political proclivity, etc. A personal profile can be built upon this analysis and recommendation will be done accordingly. Personal profiles will also be made based on the user’s demographic information and social status.

8.5 Enriching our daily life

The future RS will get into our regular lifestyle. They will keep a record of our habits by tracking our daily activities such as sleeping, walking, eating, breathing and collecting related data (Vázquez, 2013). In fact, RS will become an essential and ubiquitous part of our life. The wearable gadgets will track our daily physical activity. A wristband can tell how physically active we are and whether we are burning enough calories; using that feedback, the RS may recommend us a daily dose of exercise and meals. The smart fridge will detect our food habit. Based on this information, the RS will assess our health risks (e.g., heart disease, diabetes, high or low blood pressure, cancer, etc.) and accordingly prompts us to take necessary measures in lifestyle. Sleep trackers will perceive sleeping disorders and recommend some music/sound and aromas that induce healthy sleep. On the basis of health risk, a suitable health/life insurance plan might also be recommended (Vázquez, 2013). While driving, we will be guided by the recommendation of the best possible route to take based on traffic congestion and the road condition (e.g., if waterlogged after heavy rain).

8.6 Sensing the emotional state of a user

With the help of affective computing, RSs will be able to recognise the emotional state of a user and recommend services accordingly (Banafa, 2016). For example, sensing the mood of the user, the RS will recommend appropriate music, movies or books. Going further, if the RS can sense the partner’s mood also, it can recommend both of them an ideal location for spending the evening together or a restaurant to dine.

8.7 Personalised healthcare recommendation

Thanks to the IoT and internet of nano things (IoNT) (Akyildiz and Jornet, 2010) based ubiquitous and pervasive healthcare systems (Pramanik et al., 2018c, 2019), RSs will play a major role in providing better and personalised healthcare. Suitable medicines, health supplements, required lifestyle changes, etc., will be recommended timely. For instance, if the sugar level goes high, then an insulin dose should be recommended. If the user’s, who is suffering from depression, psychological health is read through affective computing (Banafa, 2016), proper anti-depression medicine can be recommended. If the RS finds from other sources that the person has a back problem, then it might recommend a suitable ergonomic chair that will help in curing the back problem. A diabetic patient should get a recommendation of food products that are sugar-free.

8.8 More ethical

We expect, the businesses will apply RSs more ethically to recommend products to the users (Tang and Winoto, 2016; Dimitris, 2016). Instead of recommending every possible item that will help them increase their sales, the products will be recommended to the users only if they really require and can afford to buy those. This will relieve users from likely distress.

8.9 Agricultural recommendation

RS has a huge role to play in the agriculture sector (Lacasta et al., 2018), but it is not yet explored effectively. Analysing the soil type and other necessities for farming, and following the market and weather predictions, the suitable corps that should be harvested (season wise) will be recommended to the farmers which can help farmer greatly.

8.10 Education and career

By studying and analysing interest, social activity, subject score and other parameters RSs should recommend the fitting course to the students (Rivera et al., 2018). Similarly, a future job RS shall not only consider the biodata but will study other parameters such as both intelligence quotient and emotional quotient, geographic location (according to health) and recommend the job/sector where the candidate will have the maximum chance of success.

8.11 Equipment maintenance

In the case of manufacturing products, by continuous remote monitoring with the help of IoT, the manufacturer can recommend the necessity of repairing or replacement of the product or equipment (Michel, 2014).

8.12 Cross-domain recommendation

Future RSs will experience a major advancement in terms of cross-domain recommendations (Khan et al., 2017). Present RSs are somewhat good at assuming user's preference from a single domain, but they are not able to reflect the preference of one domain into some other domain (related or unrelated). For example, the present RS cannot answer – if a person likes a thriller movie, then what kind of music or book he will prefer. The future RSs will have a unified model of preference for any user that will be effective across different domains.

8.13 Crowdsourced recommendation

Recommendation engines apply machine learning and other AI techniques to understand the preferences of the users (Ignatov et al., 2014; Safran and Che, 2017). But in spite of remarkable advancement in AI, it has not yet reached even closure to human cognitive ability. Computing might be better in performing computational jobs quickly, but humans are far better in cognition-related jobs such as identifying an image or understanding natural language. There are some problems which require both – faster processing as well as intelligent and accurate interpretation. These applications are enhanced by applying human input in addition to the usual computing algorithm. This type of computing is called human computing or crowdsourced computing (when inputs from the mass are fed into the system). Future RSs also will be enhanced by incorporating this idea for better and precise recommendations. The computers will be used to process the non-text ratings whereas human computation will process the ratings and reviews that are in text and image forms. Other human-induced knowledge, such as trends that are yet to materialise as the digital data, can also be incorporated in the recommendation process. This will certainly add value to the diversity and quality of the recommendation.

No doubt the future RSs will have a significant social impact. But as with every good thing there comes some inevitable hitches, the future RS is also no exception. The excessive uses of RS may seem to be too meddling. The major challenge in designing the RSs will be to restrict them to be irritatingly interfering in the personalised domain. On the other hand, existing RSs are generally generic in nature. They do not really reflect each user's individualised taste. So, the future RS designers have to set a balance between the two, i.e., it will neither be too generic nor too intrusive.

9 Conclusions

Making a choice among numerable options and based on the gigantic amount of online data is always going to be a tough and confusing task. Online RS help us to overcome this. To do its job competently and accurately, RSs exert efficient information retrieval and filtering mechanisms. Over the past years, immense research work has been devoted to meet these ends, and several recommendation approaches and techniques are proposed. In this paper, an overview of the different recommendation approaches used in RS such as content-based, collaborative, demographic, hybrid, knowledge-based, and context-aware recommendation has been depicted. Various problems faced while designing and implementing RS systems such as limited content analysis, over-specialisation, cold start, sparsity, scalability, synonymy, abbreviation, long tail, and black box problem are also briefly described. Different information retrieval techniques such as machine learning, logistic regression, decision tree, association rule learning, cluster analysis, Bayesian network classifier, support vector machine, LDA, TF-IDF, and deep learning are also mentioned briefly. The main objective and major focus of this paper is to track down the RS research trends. Some interesting statistics have surfaced. For instance, the majority of the research in RS is focussed on CF and knowledge-based approach. The top contributing country in RS is China. And the majority of the papers are published by IEEE. It is also observed that RS research reached its peak during the period of 2013–2014. After that, probably due to saturation, the popularity of research in this field has gradually been declined. But we believe the RS research is not dead yet. The technologies such as IoT, AI, and cognitive computing have given it a fresh vivacity. We are optimistic that in near future research on RS will witness several new and innovative avenues.

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