Machine Learning Techniques for Recommender Systems – A Comparative Case Analysis

Binu Thomas¹, Amruth K John ²

¹Associate Professor, Marian College Kuttikkanam (Autonomous)
binu.thomas@mariancollege.org
²Associate Professor, Marian College Kuttikkanam (Autonomous)
amruth.john@mariancollege.org

Abstract. Recommender System (RS) is one of the most popular applications of Artificial Intelligence which attracted researchers all around the world. Many machine learning algorithms are used to develop RSs. Choosing the best machine learning algorithm to provide users with a product or service is the most challenging task in the area of RSs. Now we are witnessing a paradigm shift in the purchase habits of people from in-shop to online resulting in the availability of online information exponentially growing every day. The ever-increasing online information and the number of online users create new avenues in RS. In an online shopping scenario, these systems must be able to recommend relevant items to the users. The RSs have to deal with the huge amount of information by filtering the relevant information based on the analysis made on the inputs made by the users during their online sessions. These systems can recommend appropriate items to users based on their interest and previous preference which can lead to increased sales. The three major techniques used to build a RS are content-based, collaborative based and hybrid-based. This paper presents the various applications of RSs and makes a detailed comparative study of different machine learning approaches used. The methodologies used for identifying research articles for analysis, the merits and demerits of different techniques in RSs and domain-specific applications of these techniques are well explained here with scientific review analysis.

1. Introduction

The Recommender Systems (RSs) are used in various domains like e-commerce, tourism, health, e-Learning, etc. These systems are widely used in the e-commerce field to recommend items to users of their interest. The items are recommended based on the buying history of customers. Based on the analysis, predictions can also be made on user preference. This technique can be considered as part of personalization because it helps each customer to buy products of his interest. This system can establish a good relationship with customers and can increase the sale rate if the recommendation is appropriate.

The RS in the e-commerce field has gained the attention of the business community. Amazon makes use of the RS to suggest the books frequently purchased by customers. Most of the RSs available today are based on the collected information of user’s purchase history, explicit rating, and ownership data but no system is using all these simultaneously.

The development of RS can also contribute to the field of tourism. They guide tourists to manage huge information and allows them to take appropriate travel decisions. This system can suggest a suitable place
that can match the appropriate activities to their profile. RSs are widely used as playlist generators for video and music services like Netflix, YouTube and Spotify. Amazon and social media platforms such as Facebook and Twitter make use of product recommenders. This system is one of the most successful applications of machine learning technologies in business. This helps the users to take quick decisions making in their online transactions and also improves the quality of their shopping experience.

These systems have also become significant in healthcare that can recommend healthcare information to patients as well as to health professionals depending on their requirements. The RS offers several opportunities in the medical field by using different machine learning techniques. The complex problems using unstructured data can be efficiently solved using different machine learning techniques.

Numerous works have been reported in the area of recommender systems for different applications like Movie recommendation, e-commerce, healthcare, etc. The recommendation in the e-Learning environment plays an important role in providing the accurate and right information to the learners. In the present scenario, e-Learning is completely transforming the learning habits of students and even adults. Intended learners are normally confused with the enormous number of courses available an online and keeping track of the relevance of these courses is also difficult. Since a huge amount of information is available on the internet, learners face the problem of searching for the right information and online recommendation system can solve the problem of information overload efficiently. This paper is an attempt to review the techniques used for RSs, the application domain areas of these techniques, merits and demerits of these techniques. In this paper, Section II introduces the methodology adopted in this study for the selection of source articles and reviews. Section III contains the literature review and a detailed discussion of merits and demerits. Evaluation matrices and domain areas are discussed in section IV. Finally, Section V concludes the paper.

2. Methodology
The review work of this paper accommodates the following phases for a systematic review of the literature. Fig.1 presents a specific set of steps followed in the management of this review paper.

2.1 Research questions and Research String
The main purpose of this literature review is to comprehend what issues RSs could successfully address, how they are developed and evaluated, and in what ways or aspects they could be experimented with. To this end, we defined the following research questions:

Q1 What are the most relevant studies about RS?
Q2 Which data mining and machine learning techniques are used in RS?
Q3 What are the problems and challenges faced in RS?

Fig 1. Structure of the review process
Q4 How RS are evaluated?
Q5 Which are the specific domain areas where RS is used?
Q6 Which directions are most promising for future research?

We picked five digital libraries as the source of research papers under review (Fig.1). The strings RS Applications, RSs Techniques, Review of RSs are used for retrieving the research papers. A total of 27580 research articles were listed by the search from the digital libraries mentioned. We have included papers from three specific periods (2001-2005), (2009-2012), and (2016-2020) to review the initial stages, subsequent progress, and present situation in RSs. Only journal research papers and conference proceedings written in English are considered for the analysis. This resulted in the selection of 1450 research papers. In the next step, we used a fuzzy based technique for assigning scores to these papers based on the three parameters: Relevance, RS Techniques, and Domain Area. A fuzzy-based score between 0 and 1 is given to the papers in each category and research papers getting a score of 0.7 or above are retained for analysis (expr. 1).

\[ \text{Paper Score} = \frac{\sum_{i=1}^{3} S_i}{3} \quad \text{expr. 1} \]

Where \( S_i \) is the fuzzy score given for a paper in a category. Based on this selection criteria 42 research papers were selected for further analysis. The sources of these research papers are represented in Fig.2.

The percentage of papers selected on the basis RS techniques as the selection criteria is represented in Fig.3.
3. Literature review

This paper presents a systematic literature review in the field of various RSs. The commonly used applications, recommendation techniques, and machine learning algorithms are discussed here. These works depict how RSs can provide personalized recommendations to online users so that they can reduce the time and effort in selecting the items or services according to their preferences. This section addresses the first Research Question and introduces the relevant studies in the area.

The study by Kumar [1] on the RS established that the recommendation system is an efficient tool to suggest recommendations on services to customers. Social media like Facebook, Google, Amazon, and Twitter proved that well-designed RS can provide accurate information to a large number of users. Item-based collaborative filtering algorithm is the commonly used technique in Amazon.com.

This technique can measure the number of users and the number of items independently. When using item-based collaborative filtering, we make a comparison between purchased and rated items of the user to related items. Then similar items are added to the recommendation list [2]. As per the study [3], it is observed that major problems in item-based RSs are the impact of context awareness, loss of neighbor transitivity, and sparsity.

The most commonly used classification of RSs is based on content-based, collaborative filtering, knowledge-based, and hybrid methods [6]. Content-based RS relies only on the past references of users
to create their profile and to select the recommended items. But in collaborative filtering, it examines the behavior of similar users to identify the candidate items. The knowledge-based RS uses domain-specific knowledge for matching user requirements with items of possible interest. The hybrid recommender is the one that combines multiple approaches to produce the output. The purpose of combining different approaches is to improve the accuracy of the recommendation.

In most of the tourism RSs, collaborative filtering and hybrid approaches [4, 5] are used. Most of them use both explicit and implicit methods to identify user interest [7]. In this domain, the tourist details are recommended using a semantic network by combining collaborative filtering and content-based filtering. The criteria include location, attraction type, price and time of travel, etc. A collaborative filtering approach is used for identifying user’s interests and their ratings to attractions explicitly and the information of the user’s social network is collected implicitly [9]. The location, time, and weather are used as the recommendation criteria. Another recommendation system in tourism based on a collaborative filtering approach and implicit criteria has been proposed by Yang and Marques. The two major issues of scalability and efficiency which need modern processing space and speed optimization to maintain user satisfaction are discussed here. In this work, collaborative filtering is used to build RS which can use the user ratings, information, and feedback collected from users to build recommendations [10].

The k Nearest Neighbours (kNN) recommendation algorithm is the commonly used algorithm in the recommendation processes using collaborative filtering. It is simple and can produce accurate results. But the low scalability [11] and sparsity [20] are the major drawbacks of this algorithm. The kNN algorithm focuses on similarity measures. The similarity calculation is performed between user to user, item to item, and user to item. By using similarity measures, similar users are assigned as neighbors to the user and items.

Major drawbacks found with the tourism RS are interactivity, adaptivity, and personalization. Even though it suggests user preferences, this system still needs user’s help to plan their trip manually. The inability of automatic travel planning is the major problem to be addressed here. The social information and context of the user can be used to solve the problem. The major approaches like collaborative, content-based, and demographic approaches suffer from personalized recommendations. The hybrid techniques can be used to solve these problems of individuality.

Healthcare RS also makes use of a collaborative filtering approach to categorize diseases, based on symptoms and then suggest appropriate doctors to patients. While using a collaborative or a hybrid filtering approach, the RS must collect information about users to build recommendations [12]. One of the most popularly used machine learning algorithms in the healthcare industry is support vector machines. It works on a supervised learning model for classification, regression, and detection of outliers. This algorithm could predict the early symptoms and medicine for heart patients and help in saving the lives of millions of patients. This can also be used for protein classification, image segregation, and text categorization.

The following sections introduce some of the specific techniques, algorithms used in RSs. A detailed analysis of the performance evaluation of these methods is presented here and this section focuses on the second Research Question.

3.1 Singular Value Decomposition (SVD)

In data science, Singular Value Decomposition (SVD) is a standard technique for reducing dimensionality and SVD lays the foundation for RSs. This method is useful for the formation of latent factors (predictions) in the scope of RSs to resolve the problems faced by the approach of collaborative filtering [2]. The key attractions of this approach are scalability and predictive precision [3].

3.2 Convolutional Neural Network (CNN)
It is a type of neural network consisting of convolution layers capturing global and local computational characteristics to enhance efficiency and precision [2]. For modeling sequential data, this network is used.

3.3 Restricted Boltzmann Machine (RBM)

The RBM is an artificial neural generative stochastic network that discovers a distribution of probability over a set of inputs. It is a neural network of two layers that consists of a visible layer and a hidden layer [25,26]. The visible and secret layer does not interact with the intralayer. It utilizes approximation algorithms for gradient descent, such as contrastive divergence. This network is used for extraction operations in a supervised learning algorithm. These models are energy-based model, as shown in Fig 5, consisting of binary-valued hidden and visible units. The strength of the relation between the noticeable and hidden units \( V_i \) and \( H_j \), respectively, is denoted by the weight matrix \( W \). For these units, it incorporates bias weights. Increasing the number of hidden units contributes to the better performance of the model.

Social network analysis (SNA) has been included in RSs as a result of the rapid growth of social networking resources in web-based systems [32, 33]. To enhance the user experience, RSs provide users with suggestions on their ability to communicate with other users in social interaction, such as online messaging, social comments, etc. These systems provide opportunities to make recommendations by using the social ties of users, especially for systems whose rating information is too scarce to perform Collaborative Filtering (CF). To present collaborative partnerships, Palau et al, [32] organized social networks and suggested steps to clarify how the Recommendation Process achieves collaboration.

Electronic government (e-government) [32] refers to the use of the Internet and other information and communication technologies to assist governments in providing better information. It is a conventional field for RSs in governance to propose web sites, documents, and news since such tools are growing rapidly. In most cases, the textual content is defined as a list of keywords that can be extracted from historical records, URLs and search engines, such as news, emails, documents and web pages, and many RSs are built based on the analysis of keywords and services for people and companies. An RS was proposed to help voters make choices in the e-election process [34], which uses fuzzy methods of clustering and offers information about candidates similar to the preferences of voters. To improve the trade exhibition RS for e-government, a hybrid fuzzy [36] logic-based recommendation system was developed.

Since these services expand rapidly, recommending websites, documents and news is a typical field for RSs. In most cases, a list of keywords that can be extracted from historical data is represented as textual content, such as news, emails, documents, and webpages. Based on keyword analysis, URLs, and RSs are constructed for search engines. In this field, probabilistic models such as the information retrieval techniques [37] are used. With each variable representing a keyword that takes into account frequency and location, contextual resources are converted into a vector (title or plain text).
e-Learning has become an important part of the education system [2] now. The user-based collaborative filtering algorithm is selected as the primary recommendation algorithm for online education [13]. Collaborative filtering based approaches give importance to the ratings given to items by users as the primary source of information for recommended learning. In many of the learning applications, the ratings are found very sparse and this causes collaborative based methods to reduce its performance in the recommendation.

The table below (Table 1) describes the various techniques used in different RSs. Based on the implementation techniques, the RSs can be divided into two, memory-based and model-based [4]. The memory-based method accesses the internal system database directly, whereas the model-based method uses the transaction data to create a model which can generate recommendation [14]. By accessing the database directly, the memory-based method is adaptive to data changes but requires large computation time depending on the data size [16]. The model-based method has a constant computing time regardless of the data size but not adaptive to data changes.

3.4 User-Based Collaborative Filtering (UBCF)

The UBCF method chooses clients with a comparable rating to a given thing as a client set [3]. It can foresee the client's appraising to another thing as indicated by others evaluating in a similar client set. The most testing undertaking of this calculation is to locate the best client set for the chose client. The principle center is to distinguish the neighbors with the most extreme similarities with the chose clients [15]. In the wake of distinguishing the likeness of the client to other people, the comparable neighbors of clients as indicated by the closeness will be chosen and assembled into neighbor records [3]. The client appraisals to explicit things can be anticipated with the assistance of the rating history of neighbors to acquire the proposed suggestion results.

3.5 Item-Based Collaborative Filtering (IBCF).

To compare the comparability of different objects, the IBCF approach is used. This is used to predict a user’s rating of a related item based on his current item rating [3]. Model-based methods can recommend items with the highest rank to a user, returned by the parametrized model [6]. The most popular algorithm in this category is the Slope one method. It is a linear regression model that learns through a set of simple predictors, one for each pair of two items with just one constant variable [17] so that this variable can represent the average difference between the ratings of two items. This method has fast computation and reasonable accuracy.

3.6 Matrix Factorization

These are the most successful latent models that can solve high sparsity problems. Matrix factorization became popular because of its enhanced scalability and predictive accuracy [18]. One of its significant contributions is its ability to uncover the hidden structure behind data. It is an effective technique used for information retrieval.

Using Matrix Factorization, the content-based filtering recommendation algorithms can be modified to a new algorithm called content-based filtering recommendation algorithm using HMM (Hidden Markov Model). The average precision of the HMM-based algorithm is higher, hence this algorithm is recommended for personalized systems [19].

3.7 Computational intelligence-based recommendation techniques (CI)

Computational intelligence approaches are commonly used in RSs to create recommendation models. Bayesian techniques, artificial neural networks, clustering techniques, genetic algorithms, and fuzzy set techniques are used in these CI approaches. For model-based RSs [32], Bayesian classifiers are popular and are often used to derive the Content-Based (CB) RSs model. Each node corresponds to an object when implementing a Bayesian network in RSs, and the states correspond to each possible vote value. For each object, there will be a collection of parent items within the network that represent its best
predictors. As a basis for integrating both CB and CF methods, a hierarchical Bayesian network has also been introduced [36].

Table 1. Comparison of Recommendation System techniques

| Techniques                      | Representative algorithm | Advantages                                                                 | Disadvantages                                                                 |
|---------------------------------|--------------------------|-----------------------------------------------------------------------------|------------------------------------------------------------------------------|
| Memory-Based Collaborative Filtering (CF) | User-Based CF, Item Based CF | Simple to execute, Data addition is simple, Content should not be considered, Efficient scalability | Depends on the explicit suggestions, Cold start issue, Trouble with Sparsity, Scalability limited for huge dataset, Model is costly, Loss of information in a factorization matrix |
| Model-Based Collaborative Filtering | Slop-one CF            | Enhances the efficiency of prediction, Improves issues with scalability and sparsity |                                                                                |
| Hybrid Collaborative Filtering   | Combination of memory-based and model-based. | Overcome the sparsity limitations, Enhances the efficiency of prediction. | Complexity is increased, Challenging for implementation.                     |
| Content-Based Filtering          | Content-Based filtering algorithm using Hidden Markov Model | No issue with scarcity and cold start, It ensures confidentiality. | Needs detailed description of items, Requires ordered user profile, Concern is material overspecialization. |
| Hybrid Filtering                 | Combination of Collaborative and content-based algorithm | Collaborative and content-based methods are complementary strengths and shortcomings. | Difficult to implement                                                        |
| Computational intelligence-based | Combination of Fuzzy Logic Neural Network Artificial Intelligence | It eases the overload of information, improves the processing of information and solves new problems. | Failure to predict correct results for varying situations, Poor in providing optimal shedding of load. |

An Artificial Neural Network (ANN) is an interconnected node and weighted connection assembly that is inspired by the biological brain's architecture and can be used to create model-based RSs [35].

4. Discussion

4.1 RS Techniques and Challenges
RSs will provide users with personalized and targeted suggestions [38]. Therefore, they address the problem of data overload that plagues the users of the digital era. Different methods have recently been developed for building RSs, which can use either collaborative filtering, content-based filtering, or hybrid filtering. The technique of collaborative filtering has achieved a certain maturity and is one of the systems most frequently implemented. Content-based filtering techniques usually base their predictions on user data and, as in the case of collaborative techniques, they disregard contributions from other users. Although content-based filtering techniques have problems such as restricted content analysis, overspecialization is very important. The challenges and limitations with content-based recommendations [23] are discussed in the following section and it addresses Research Question 3.

Over Specialization: The system does not suggest the items that are different from the item that the user has seen before. This may create a problem because the user wishes to try something new and the system may not allow this to work. So it is advised to make several options available to the user.

Limited content analysis problem – In this problem, we may represent two different items with similar attributes so that they cannot be distinguished.

New user problem: Since new users do not have enough ratings, the system may not be able to make accurate recommendations such a user.

It is advised to use Content-based filtering when there are limited users and fewer user items. The Collaborative Filtering method is best used when there is a large number of users and items [24]. The major drawbacks identified with Collaborative filtering techniques are listed below

Cold start – It is difficult to give suggestions to the new users because the system is not familiar with the new user’s interests. This problem can be solved by surveying at the time of the users profile creation. Questions can be posed and based on the user’s responses recommendations can be made.

Scalability – When there is a large number of users available, more resources are needed for information processing. The resources are spent to determine users with related purchasing patterns. This problem can be solved by using different types of filters.

Scarcity – A large number of users and items are available on online websites. Collaborative and other RSs can create a neighborhood of users using their profile using various recommendation techniques. If the user rates only a few items, it will be difficult to find out the user’s interests and will be mapped to the wrong neighborhood. This is called a Data sparsity or scarcity problem.

Privacy – It is another major issue to be discussed in this system because the RS has to collect information like user location, bank data, etc. All online websites must make sure that the algorithms used can ensure data protection.

Another problem faced by the RS is Longtail items, the ones rated by fewer users. To solve this problem, it is important to consider other aspects like diversity along with accuracy.

This paper presented various algorithms and techniques used to build RSs. The algorithms and approaches discussed here have their advantages and disadvantages like user-based approaches are precise but not scalable, item-based approaches are scalable but not precise. Hybrid RS combines the best features of user-based and item-based algorithms but they are complex too. In this scenario, evaluation matrices are used to assess the effectiveness of RSs. This section focuses on Research Question 4.

4.2 Evaluation matrices

The most prominent evaluation metrics in the research literature measure the accuracy of the system's predictions. Accuracy is measured as the magnitude of error between the predicted value and the true expected value. Predictive accuracy is the RS’s capacity to predict the expectations of a consumer for an
object. Mean absolute error is the traditional approach for calculating predictive precision (MAE). It is the absolute average difference between the estimated values and a user's real expected value.

The other possible evaluation metrics are listed below:

Novelty: A CF system can recommend items that the user was not aware of before. For many applications, novelty is one of the most valued characteristics of the CF system's recommendations. A system tuned for novelty will actively avoid recommending new stories that already a user has awareness.

Serendipity: Users are given recommendations for items that they would not have seen through their existing channels of discovery. A serendipitous scheme would imply news stories on subjects that have never been read about before. Researchers have researched how algorithms can be modified to facilitate serendipity and novelty [27], but it is difficult to quantify novelty because it involves live user trials where users indicate whether a suggestion is a novel.

Coverage: It is the proportion of the CF system's items known for which predictions can be made by the CF system. Variants such as the percentage of products that have the potential to be recommended to users can also be measured, as performance optimizations in recommendations can prevent certain items from ever being recommended [28].

Learning Rate: It tests how fast the CF system becomes an efficient taste indicator as information starts to arrive. These are calculated per-user, measuring the number of ratings a user has to provide before they receive personalized predictions of high-quality [29].

Confidence: It defines a CF system's ability to determine the likely quality of its predictions. Most CF systems produce rankings based on the expected rating that is most likely. A CF system that can accurately measure its confidence in a forecast can restrict recommendations to high trust, leading to a trade-off between fewer false predictions at the expense of reduced coverage and probably reduced novelty. Trust in predictions is measured in certain instances and shown to users to help them determine if the risk-return ratio is appropriate [30].

User satisfaction metrics: The metrics mentioned above are just a sample of potential metrics for assessment. There are several more metrics, in particular, that researchers may create. These metrics will provide users with a system, and calculate how the system is viewed by users. It is typically achieved either by surveying the consumers or by calculating statistics for retention and usage.

4.3 Application Domain Areas
RSs and their applications reviewed in this paper are presented in Table 2. Here Research Question 5 is addressed and summarized. From the summary of RSs, the following important findings can be extracted: The major techniques used in the recommendation system are CB, CF, and Hybrid techniques, among these, Hybrid techniques are most popular. The CF techniques are widely used in e-resource RSs. The e-learning RSs have highly applied knowledge-based techniques. The social network-based RS and context awareness-based RS has also played a major role in recent application developments.

Computational intelligence methods, such as fuzzy logic, are used to deal with different uncertainties in all kinds of RSs. KB techniques, such as ontology and semantic tactics, are commonly incorporated with CF and CB recommendation methods into e-business RSs [31, 32]. The key explanation for this is that there is a high need for domain information in e-businesses [41] to help their recommendations.
Table 2 RS Techniques and application domain areas reviewed

| Techniques    | CB | CF | KB | Hybrid | Computational Intelligence | Social Network | Context-Aware | Group Aggregation |
|---------------|----|----|----|--------|-----------------------------|----------------|--------------|------------------|
| E-government  | 1  | 3  | 1  | 4      | 4                           |                |              |                  |
| E-business    |    |    |    |        | 1                           |                |              |                  |
| E-commerce/E-shopping | 3 | 1 | 4 | 1 | 4 | 2 | | |
| E-library     | 2  | 2  | 3  | 1      |                            |                |              |                  |
| E-learning    | 2  | 11 | 2  |        |                            |                |              |                  |
| E-tourism     | 5  | 9  | 9  | 3      | 2                           | 11             |              |                  |
| E-resource    | 9  | 16 | 6  | 15     | 8                           | 1              | 1            | 1               |
| E-group Activity | 9 | 5 | 2 | 5 | 1 | 2 | | |
| Total         | 31 | 37 | 36 | 40     | 27                          | 6              | 12           | 2               |

While RS applications have achieved great growth, there are still some problems that need more research with the advent of new applications for e-services. The hybrid recommendation approaches which combine CB, CF, and KB techniques are widely used in the e-library RSs. There are several cases, such as suggesting a TV program to a group of individuals who are unable to determine their users. In tourism scenarios, users need to negotiate online to engage in an activity together [39]. In these situations, for a whole community, individuals need online decision support. Traditional RSs make suggestions only for individual users, so it is suggested that community RSs (GRS) combine and match the individual preferences of group members to provide the group with satisfactory recommendations [42].

It is now possible to give customized and context-sensitive suggestions to mobile users with the increasing usage of Internet-accessing smartphones, and more mobile RSs would be needed. However, mobile data, which is heterogeneous, noisy, requires spatial and temporal auto-correlation, and has validation and generality issues [32,37] is typically more complex. Further Mobile-based analysis in the field of RS could make a significant contribution.

5. Conclusion
From the review of RSs, it is observed that there is an exponential growth of research in this field. Collaborative filtering is the most popular technique used for recommendation systems but the major drawback with this approach is its inability to solve the cold start problem. The commonly used technique next to CF is content-based filtering, but this technique also suffers from the same problem. Hence the hybrid approach, combining the other two techniques seem to produce a better result and it is becoming the most popular technique adopted in RSs. With the ever-increasing online usage in all aspects of human life due to the present pandemic situation, novel artificial intelligence-based systems are evolving in this area. In this paper, we have discussed the existing generation of RSs. There are possible extensions to these algorithms which can lead to more fruitful researches in this area.
References:
[1] F G. Adomavicius and A. Tuzhilin 2015 Context-aware RSs  Recomm Syst Handbook, Second Ed. 191–226
[2] Murad, D. F, Heryadi, Y, Wijanarko, B. D, Isa, S. M and Budiharto 2018 Recommendation system for smart LMS using machine learning: a literature review Proc. Int. Conf. on Computing, Engineering, and Design (ICCED) IEEE 113-118
[3] Venkatesan R and Sabari A 2020 Issues in various RS in E-commerce 2020 - A survey 2020 Journal of Critical Reviews 7(7) 604-608
[4] Sahoo, A. K, Pradhan, C, Barik, R. K and Dubey H 2019 DeepReco: deep learning based health RS using collaborative filtering. Computation 7(2) 25
[5] Sharma, M, Chauhan, N, Bansal, H and Stanciu L 2020 Digital Marketing and AnalysisTechniques: Transforming Internet Usage New Age Analytics 1
[6] Çano E and Morisio M.2017 Hybrid RSs: A systematic literature review. Intelligent Data Analysis 21(6) 2017 Esmaeili, L, Mardani, S, Golpayegani, S. A. H and Madar, Z. Z 1487-1524
[7] Leila Esmaeili and Shahla Mardani et al 2020 A novel tourism RS in the context of social commerce Expert Systems with Applications Volume 149 ISSN 0957-4174
[8] Alamdari, P. M, Navimipour, N. J, Hosseinzadeh, M, Safaei, A A and Darwesh A 2020 A Systematic Study on the RSs in the E-Commerce IEEE Access 8 115694-115716
[9] Singh, P. K, Dutta, P. K, Pramanik, A K D and Choudhury 2020 P RSs: An Overview, Research Trends, and Future Directions, International Journal of Business and Systems Research
[10] Li-Tung, Yue Xu and Yuefeng Li 2005 A framework for e-commerce oriented RSs, Pro. Int. Conf. on Active Media Technology. Kagawa, Japan 309-314
[11] Xue, G. R, Lin, C, Yang, Q, Xi, W, Zeng, H J, Yu,Y and Chen Z 2005 Scalable collaborative filtering using cluster-based smoothing Pro. Int. Conf. on Research and development in information retrieval 114-121
[12] Shih, Y. Y and Liu D. R 2005 Hybrid recommendation approaches: collaborative filtering via valuable content information Proc. Int. Conf. on System Sciences 217b
[13] Sikka, R, Dhankhar, A and Rana C 2012 A survey paper on e-learning RS. International Journal of Computer Applications 47(9) 27-30
[14] Sarwar, B, Karypis, G, Konstan, J and Riedl J 2001 April Item-based collaborative filtering recommendation algorithms Proc. Int. Conf. on World Wide Web 285-295
[15] Dou, Y, Yang, H and Deng X 2016 A survey of collaborative filtering algorithms for social RSs Proc. Int. Conf. on Semantics, Knowledge and Grids (SKG) IEEE 40-46
[16] Thorat, P. B, Goudar, R. M and Barve 2015 S Survey on collaborative filtering, content-based filtering and hybrid recommendation system. International Journal of Computer Applications 110(4) 31-36
[17] Dou, Y, Yang, H and Deng X 2016 A survey of collaborative filtering algorithms for social RSs Proc. Int. Conf. on Semantics, Knowledge and Grids (SKG) IEEE 40-46
[18] Ravi, L and Vairavasundaram S 2016 A collaborative location based travel recommendation system through enhanced rating prediction for the group of users Computational intelligence and neuroscience
[19] X Luo, Y Xia and Q Zhu 2012 Incremental Collaborative Filtering recommender based on Regularized Matrix Factorization Knowledge-Based Systems vol 27 271–280
[20] J Bobadilla and F. Serradilla 2009 The effect of sparsity on collaborative filtering metrics in Proc. Int. Conf. on Database (ADC ’09) 9–17
[21] Li, H, Cai, F and Liao Z 2012 Content-based filtering recommendation algorithm using HMM Proc. Int. Conf. on Computational and Information Sciences IEEE 275-277
[22] Z Gao Z Li and K Niu 2016 Solutions for problems of existing E-Commerce recommendation system in Consumer Electronics- Taiwan(ICCE-TW) Proc. Int. Conf. on IEEE 1-2
[23] Soanpef Sree Lakshmi et al 2014 (IICSIT) International Journal of Computer Science and Information Technologies RSs: Issues and challenges Vol 5(4) 5771-72
[24] Siddhesh Jagtap, Yash Mane, Tushar Kadam and Trupti Dangge 2019 Survey paper on RSs Volume:06 Issue:12 Dec 2019 International Research Journal of Engineering and Technology (IRJET)
[25] Yedder, H B Zakia, U Ahmed, A and Trajkovic, L 2017 Modeling prediction in RSs using restricted boltzmann machine IEEE Proc. Int. Conf. on Systems Man and Cybernetics (SMC) Banff AB Canada 5–8
[26] Belle, A, Thiagarajan, R, Soroushmehr, S M, Navidi, F, Beard, D A and Najarian K 2015 Big data analytics in healthcare Biomed Res. Int. 370194
[27] Karypis G 2001 Evaluation of Item-Based Top-N Recommendation Algorithms Proc. Int. Conf. on Information and Knowledge Management (CIKM) 1 247-254
[28] Sarwar, B Karypis, G, Konstan and J.A Riedl 2000 J Application of Dimensionality Reduction in RS- A Case Study ACM WebKDD Web Mining for E-Commerce Workshop Boston Massachusetts
[29] Schein, A I, Popescul, A, Ungar and L H 2001 Generative Models for Cold- Start Recommendations Proc.Int. Conf. ACM SIGIR Workshop on RSs New Orleans Louisiana
[30] Schafer J B, Frankowski D, Herlocker J and Sen S 2007 Collaborative Filtering RSs. In: Brusilovsky P, Kobsa A, Nejdl W (eds) The Adaptive Web Lecture Notes in Computer Science vol 4321 Springer Berlin Heidelberg
[31] D Ben-Shimon A, Tsikinovsky, L Rokach, A Meisles, G Shani and L Naamani 2007 RS from personal social networks Advances in Intelligent Web Mastering Springer 47-55
[32] Lu, J, Wu, D, Mao, M, Wang W and Zhang G 2015 Recommender system application developments: A survey Decision Support Systems 74 12–32
[33] X Guo and J Lu 2007 Intelligent e-government services with personalized recommendation techniques International Journal of Intelligent Systems 22 401-417
[34] L Terán and A Meier 2010 A fuzzy RS for eElections in: K. Andersen, E Francesconi Å Grönlund T van Engers (Eds.) Electronic Government and the Information Systems Perspective Springer Berlin Heidelberg 62-76
[35] P De Meo, G Quatrone and D Ursino 2008 A decision support system for designing new services tailored to citizen profiles in a complex and distributed e-government scenario Data and Knowledge Engineering 67 161-184
[36] N Zheng and Q Li 2011 A RS based on tag and time information for social tagging systems Expert Systems with Applications 38 4575-87
[37] R Jäschke, L Marinho, A Hothon, L Schmidt-Thieme and G Stumme 2007 Tag
Recommendations in folksonomies in: J Kok, J Koronacki, R Lopez de Mantaras, S Matwin, D Mladenčič, A. Skowron (Eds.) Knowledge Discovery in Databases: PKDD Springer Berlin Heidelberg 506-514

[38] A Hotho, R Jäschke, C Schmitz and G Stumme 2006 Information retrieval in folksonomies: search and ranking in: Y Sure J Domingue (Eds.) The Semantic Web: Research and Applications Springer Berlin Heidelberg 411-426

[39] J Gemmell, T Schimoler, M Ramezani, L Christiansen and B Mobasher 2009 Improving folkrank with item-based collaborative filtering Proc. of the ACM RecSys’09 Workshop on RSs and the Social Web ACM New York NY USA

[40] X Amatriain, A Jaimes, N Oliver and J Pujol 2011 Data mining methods for RSs in: F Ricci, L Rokach, B. Shapira, P B Kantor (Eds.) RSs Handbook Springer US 39-71

[41] K Yu, V Tresp and S Yu 2004 A nonparametric hierarchical bayesian framework for information filtering Proc. Int. Conf. on Research and Development in Information Retrieval ACM Sheffield United Kingdom 353-360