Proceedings of the World Congress on Engineering and Computer Science 2018 Vol I
WCECS 2018, October 23-25, 2018, San Francisco, USA

Analysis and Implementation of Recommender System in E-Commerce

Shubha C A, Shubha Bhat, Anjan K Koundinya, Ashutosh Anand, Loyel Robin Nazareth, Shashank K and Venkatesh Prasad N S

Abstract— Astounding growth of E-Commerce in the business arena, is the outcome of boundless exploration in the field of Recommender Systems (RS). RS's have increased customer engagement of Video Streaming applications by 23% and have a market of over 450 billion dollars. The immense growth of products as well as customers poses crucial challenges to RS. Millions of customers and products exist in the E-Commerce scenario and are generating high quality recommendations. To perform several recommendations in a fraction of second is a demanding and compelling task. The aim of this paper is to analyze various techniques that fetch personalized recommendations in e-commerce systems which are web based. Evidently, three techniques could be used to calculate the prediction values for a given set of users and items. Collaborative filtering technique, content based filtering technique and a hybrid approach persists in the realm of recommendations. For a large user base consisting of several transactions, analysis of RS will be outcome of thorough scrutiny of memory and model based algorithms. The dimensionality of the data is the key for analysis of the required and relevant data for the user's context. Ultimately the best suited algorithm for the given data set is found to give recommendations to the user through an interactive web-based user interface. Finally, a convenient evaluation technique is used to check the accuracy of the recommendations generated with the algorithms.

Keywords—E-commerce, Recommender system, Collaborative filtering, Content-based filtering.

I. INTRODUCTION

A recommender system is a tool or information system that intends to provide the users with suggestions that may interest them based on the past preferences or a log of purchase, or may be demographic information. The recommender system provides each customer with the individual personalization and helps the site to adapt itself based on the user preferences. The main purpose of the recommender system is to improve the quality of the decisions made by a customer while surfing through online store and choosing the appropriate product online. For example, a user would not prefer to go through the difficulty of selecting an item from a huge inventory. Instead, would prefer someone to recommend the best items based on some criteria like the rating of the item or previously purchased items or from the favorite category of a user [1][2].

To generate an efficient recommender system, there are many techniques and approaches available for the system developers. Hence, depending on the application there could be different solutions that fit but selecting the best techniques could cause some difficulty because of change in state of the database [3].

Shubha CA , Shubha Bhat, Dept. of Computer Science and Engineering, Dayananda Sagar College of Engineering, Bengaluru, India,
Anjan K Koundinya, Dept. of Information Science and Engineering, Dayananda Sagar College of Engineering, Bengaluru, India,
Ashutosh Anand, Loyel Robin Nazareth, Shashank K and Venkatesh Prasad N S, Dept. of Computer Science and Engineering, R V C E, Bengaluru, India. E-mail: {annjank2, shubha.nhce}@gmail.com

The biggest challenge in RS is to turn the techniques selected for an application into real-time scenarios. By considering all the factors, the RS developed in the project is analyzed and examined for the best fit according to the dataset selected. The approaches used are, memory based and model based collaborative filtering.

Essentially a RS needs to make work easier for both the vendor and customer. User satisfaction is always of utmost importance to any businessman. The advent of recommendation methods in diverse fields, have captivated customers. When a technology can learn what one needs, find the similarities with the choices one has made, and then make a prediction based on the similarities that exist in the customer's usage pattern, the probability of a user coming back to such place is very high. When a user is suggested items based on the similarity between his searches, such a technique is called as memory-based collaborative filtering. The same user might have a varying attitude towards different products. The user might either completely dislike a product or fully be in favor with it. The model-based algorithm learns such fluctuations in the attitude of a user towards a product and then makes almost perfect recommendations [4].

E-commerce recommendations [5] are a splendid attribute that draws attention of millions of users. Earlier there used to be limited number of products and a user had to manually search for products that interests him. But now this is a very tedious task, considering the huge number of products which exists. According to a report from economic times[23], Amazon India has over 40 million products locally and has revenue of over $16 billion in the year 2017 and this is forecasted to increase in the coming days. Hence manually searching those many products is unimaginable and impossible for a user. Hence the need for RSs has grown substantially. The presence of RSs in e-commerce makes it feasible for a user to purchase an interesting item. This in fact has multiplied the possibility of more than one order in a single transaction. Thereby leading to the profit of such e-commerce websites and user get convenient notification of the interested product if they are not available. The profit and sale of product in e- commerce websites are purely depended on the accuracy of recommender system.

II. RELATED WORK

E-Commerce is a vast business domain, where a large number of users are getting added up every day. It is important to fulfill the needs of customers as they are rapidly increasing. With the advent of the emerged internet driven systems the concept of recommendations are turning out to be a natural option to adopt. But the real task was to build a near-perfect RS from scratch or requires customization for business domain of the e-commerce company. With the evolution of various algorithms that bring out the recommendations, the quality was being improved. However, the development of such algorithms for RSs is an eternal process with changing requirements of the users and business domain. The algorithms developed have been modified a several number of times, where even a minor change to an existing algorithm has brought greater impact.

A comprehensive approach is to employ user-based collaborative filtering algorithm [1]. The user's relationship with items and similarity between users yield the desired recommendations. Using the combination of conventional similarity metrics super similar and super dissimilar users was determined. They proposed a new method Confidence based Similarity Computation to find average similar users. Eight similarity metrics were considered to find similarity between users. A preference network was made combining the confidence -confidence similarity and Mean Squared difference to produce prediction. The proposed method improved performance with regard to average mean absolute error, coverage, precision and recall.

Over 60 e-commerce recommender systems were surveyed [2] to compare, analyze and summarize the progress in the field. The author discussed about various functions of Recommender systems, simultaneously giving insights on the different algorithms. The advantages and the disadvantages of collaborative filtering technique, content-based filtering technique, hybrid recommendation technique and social network based recommendation technique were elucidated. Apparently, it was found that Collaborative filtering and hybrid approach play major roles in e-commerce and the need for contemplation of several issues like decreasing computational complexity, improving recommendation accuracy in future recommender systems was emphasized.

Presentation of an evolutionary approach [3] in collaborative filtering, when state of a database changes, the RS technique used may not be as effective as before. A different approach needs to be applied in such cases. In real world scenario, it is a very challenging and crucial task to choose a particular approach when a database changes its state. Invenire, the novel approach automated the RS selection.

The description of the various RS techniques [5] that are used comprises of algorithms for collaborative filtering and content-based technique. The general approach to recommend products to a customer is elucidated, along with the properties that define an efficient recommender system. Trust based Social recommender systems, agent based recommender systems and hybrid recommender systems are described. Paper justified the usage of reviews, rating and opinion mining for quality recommendation.

Comparison of four CF prediction methods on recommender systems [6] like Weighted-sum, mean-centering, boosted weighted sum and boosted double means centering predictions are mere metrics of RS. In the conventional weighted-sum approach the missing rating is predicted depending on the nearest neighbors and/or their ratings. This approach is erroneous. The missing rating can be found with mean-centering approach, where comparison is made with the mean rating, thereby giving less error than the traditional technique. Prediction of the missing rating is done iteratively to boost the weighted-sum approach. In the boosted double prediction, both user and item biases are taken to consideration iteratively. This is found to be the best approach with less recommendation error. That's because of the iterative prediction with the updated sample weight. It successfully overcomes the sparsity problem.

A hybrid approach that combines user-based and item-based algorithms to build a music recommender system as discussed in [7]. This new method has imported a weighting factor as its parameter and has decreased the sparsity problem. The negative impact of the problem was much lower compared to conventional CF approach. The authors considered Mean Absolute Error (MAE) to evaluate the performance of RS. Lesser the MAE value, greater is the performance of recommendation algorithm. The MAE value is much lesser in the proposed hybrid approach than the traditional user-based and item-based algorithms considered separately. More accurate prediction was obtained when the testing data increased by 25%. The prediction got optimized with increasing data.

A survey about the different recommender systems in market and comparison of different approaches in designing them is presented in [13]. After analyzing the RS algorithms like collaborative filtering, content-based filtering and hybrid process the authors listed out the challenges with each technique. Unavailability of data to recommend has also lead to problem with early recommendation to a new user. The problem that arises when number of users increase and presence of only recommendations based on previous transactions without updating new items. These challenges are called "data sparsity problem" or "cold start problem", scalability problem and over-specialization respectively.

An approach to enhance collaborative filtering algorithm on Map Reduce was proposed [14]. Information overload has resulted in the focus of research on recommender system change from stand-alone mode to server cluster. The collaborative filtering recommendation techniques are based on matrix decomposition which does not conform to very large data. Thus Hadoop which is a distributed platform can be employed for collaborative filtering algorithm. It was observed that there was improved recommendation with scaling of the data on Map Reduce framework in Hadoop. The quality of recommendations improved greatly as the tasks were distributed among nodes in distributed parallel processing. The recommender algorithm could work on massive data with the approach.

III. RECOMMENDER SYSTEM TECHNIQUES

Content based filtering [17] analyzes the content of textual information such as URLs visited or documents, already purchased items, items that have been added to wish list or items that have captured the interests of users to suggest similar items. Thus, the items that have already been bought or visited are used to create a perception about the interests of users and to obtain knowledge about their tastes and preferences.

Collaborative filtering [18] is the heart of recommendation engines in the contemporary world. It uses the wisdom of the crowd to suggest items. It attempts to find neighboring users i.e. users who are most similar to the target user and suggests items liked by those neighboring users. It employs unsupervised learning methods and can learn what features to use on its own. CF is basically divided into memory based CF and model based CF.

Memory based CF can be divided into user-user filtering and item-item filtering. User-user finds users who are similar to the current user based on the similarity of ratings and suggest items which are most liked by those users. Item-item filtering finds users, who liked the current item, find similar users and other items liked by those similar users. Model based CF uses singular value decomposition to perform feature learning. It learns product features from known ratings and also learns user preferences from item attributes and then generates its own predictions from the learned preferences. SVD is also known as matrix factorization which is used for latent variable decomposition and dimensionality reduction.

Hybrid Recommender systems [19] combine both content based and collaborative filtering approaches i.e. they use user ratings as well as content features to generate recommendations. These systems use information obtained from content based approaches to initialize user rating scores for unrated items. Thus, the predictions obtained from this method tend to be more accurate than the other approaches.Memory and model based collaborative filtering methods employ various algorithms. Memory based CF techniques use Pearson coefficient and cosine similarity to calculate prediction values [21]. Model based CF techniques use singular value decomposition for performing matrix factorization [22] [23].

A. Pearson Correlation Co-efficient

This method computes the direction as well as magnitude of each vote in comparison to the mean score of the corresponding user. It is used to handle two major problems with user ratings.

- Large number of missing ratings
- Tough raters vs. Easy raters

The Pearson co-efficient is calculated using (1)

$$r = \frac{\sum(X - X')(Y - Y')}{\sqrt{\sum(X - X')^2 \sqrt{\sum(Y - Y')^2}}} \quad (1)$$

Where, r is the Pearson co-efficient,

X and Y are user's rating,

X^' and Y^' are user's mean rating

B. Cosine Similarity

This method treats two users as vectors in n-dimensional space, where is the number of items in the database. The cosine angle between these two gives us a value between -1 and 1. Values close to -1 indicate extreme dissimilarity and values close to 1 show extreme similarity.

User-User similarity is calculated using (2),

$$s_u^{cos}(u_k, u_a) = \frac{u_k \cdot u_a}{\|u_k\|\|u_a\|} \quad (2)$$

Where, u_k and u_a are user vectors

$s_u^{cos}(u_k, u_a)$ gives the similarity between users' k and a for commonly rated items

Item-Item similarity is calculated using (3),

$$s_u^{cos}(i_m, i_b) = \frac{i_m \cdot i_b}{\|i_m\|\|i_b\|} \quad (3)$$

Where, i_m and i_b are item vectors

$s_u^{cos}(i_m, i_b)$ gives the similarity between items m and b for commonly rated items

C. Prediction Calculation Formula

User-User predictions are calculated using (4),

$$\hat{x}_{k,m} = \bar{x}_k + \frac{\sum_{u_a} sim_u(u_k, u_a)(x_{a,m} - \bar{x}_{u_a})}{\sum_{u_a} |sim_u(u_k, u_a)|} \quad (4)$$

Where, $\hat{x}_{k,m}$ is the predicted rating of item m by user k

$\bar{x}_k$ is the mean rating by user k

u_k, u_a are user vectors

$x_{a,m}$ is the rating of item m by user a

$\bar{x}_{u_a}$ is the mean rating of user a

$sim_u(u_k, u_a)$ is the similarity of user k and user a

Item-Item predictions are calculated using (5),

$$\hat{x}_{k,m} = \frac{\sum_{i_b} sim_i(i_m, i_b)(x_{k,b})}{\sum_{i_b} |sim_i(i_m, i_b)|} \quad (5)$$

Where, $\hat{x}_{k,m}$ is the predicted rating of item m by user k

i_m, i_b are item vectors

$x_{k,b}$ is the rating of item k by user b

$sim_i(i_m, i_b)$ is the similarity of item m and item b

D. Singular Value Decomposition

SVD basically decomposes a matrix into three matrices of different orders with each of them having different inferences. The winning team of the Netflix challenge used this algorithm to make predictions [24].

Single value decomposition is done using (6),

$$X = U \times S \times V^T \quad (6)$$

Given an m x n matrix X:

Where, U is an m x r orthogonal matrix

S is an r x r diagonal matrix with non-negative real numbers on the diagonal

V^T is an r x n orthogonal matrix.

E. Root Mean Square Error

This is used to calculate total error in the algorithm.

Root Mean Squared Error (RMSE) is calculated using (7),

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum(x_i - \hat{x}_i)^2} \quad (7)$$

Where, N is the number of users

x_i is the predicted rating

$\hat{x}_i$ is the rating from the testing set.

ISBN: 978-988-14048-1-7
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

IV. Experimental Analysis and Results

This paper has several evaluation metrics and other parameters that are tuned during the course of its execution. They are also used to verify whether the outputs conform to the established theories and allow programmers to explore and correct the ambiguities [21].

A. *Evaluation Metrics*

Assessment measurements are the criteria for testing distinctive calculations. The conduct of the calculations or methods can be resolved utilizing these measurements [26]. A few methods fulfill a portion of the measurements. In this venture, the yields that are acquired from the distinctive information sources given to the framework are contrasted with reality which checks whether the measurements are fulfilled. The required measurements of assessment according to that a decent procedure ought to be assessed against are:

a) **Root Mean Square Error:** RMSE calculations are used to calculate the average error in predictions. Thus, they help to evaluate the accuracy of algorithms.

b) **Sparsity Values**: Sparsity values indirectly determine the RMSE values but are not always accurate in comparing errors. By seeing the values, quality of the algorithm can be directly judged in most of the cases.

B. *Experimental Dataset*

To test the validity of any theory or proposition we need some data on which the operations can be performed. In the analysis and implementation of recommender systems for e-commerce, two types of datasets consisting of transaction details of various users from an online retail store were used. The first dataset was of an online store which consisted of details such as invoice number, stock id, product description, customer id, unit price of the product and their ratings. Out of these fields customer id, stock id and ratings were chosen for generating collaborative predictions. The second dataset was Meta data from amazon which had for each product, details of customers who bought the product, their ratings and the category to which the products belonged. From this available meta-data customer id, product id and the corresponding ratings were extracted.

1) **Online Retail Dataset:** This dataset consists of the details of transaction of 4370 users and 4067 items. From a variety of details of over 5 lakh transaction user id, customer id and their corresponding ratings were selected for analysis and implementation of algorithms. The partial dataset is organised.

2) **Amazon Meta Dataset** :This dataset consists of the details of over 15 lakh users and over 4 lakh items. It consisted of product wise details of the customers who bought the product and their corresponding ratings and the category to which the product belonged. This data had to be parsed to obtain the required fields for the algorithm.

3) **Performance Analysis of Results**

This section details performance of system on diff erent algorithms by using two different datasets based on its evaluation metrics and its sparsity values.

4) **(User x Item) vs. RMSE:** The accuracy of predictions with the changing number of users and items, is represented using RMSE values. The Table I gives the RMSE values for different user and item numbers.

TABLE I. RMSE VALUES FOR VARYING NUMBER OF USERS AND ITEMS

(User x Item)	*User-based error*	*Item-based error*	*Model-based error*
(1024 x 2879)	0.5492	0.5708	0.5631
(1664 x 3143)	0.5505	0.5663	0.5564
(2708 x 3502)	0.5538	0.5664	0.5520
(4373 x 4070)	0.5510	0.5627	0.5418

Figure1 shows the results for (user x item) vs. RMSE. As expected, with increase in the number of users and items the available experimental data for the algorithm increases leading to more accurate calculations. The dataset shows some irregularity with user-user based CF but tries to conform when the numbers still increase.

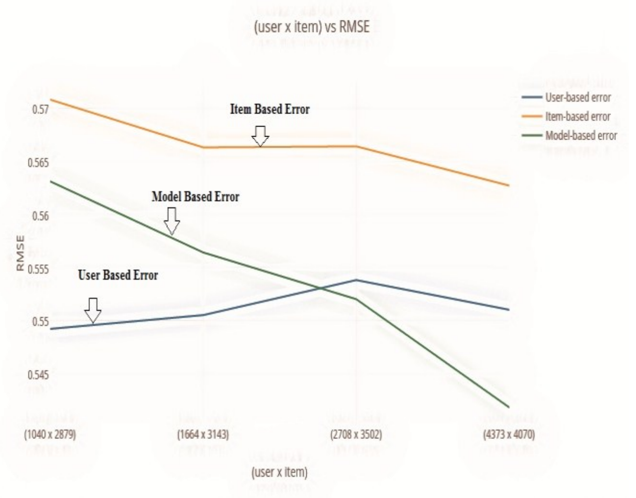

Fig. 1. User x Item vs. RMSE.

5) **Sparsity vs. RMSE:** The accuracy of predictions with the changing sparsity, is represented using RMSE values. The Table II gives the RMSE values for different sparsity values.

TABLE II. RMSE VALUES FOR VARYING SPARSITY VALUE

Sparsity	*User-based error*	*Item-based error*	*Model-based error*
98.3	0.5492	0.5708	0.5631
98.1	0.5505	0.5663	0.5564
97.9	0.5538	0.5664	0.5520
97.0	0.5510	0.5627	0.5418

Figure 2 shows the results for Sparsity vs. RMSE. Increase in sparsity values means that there are less number of users who have rated a certain product. This leads to too many zeroes in the user item matrix and hence impaired predictions. Thus, it is seen with increasing sparsity RMSE

ISBN: 978-988-14048-1-7
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

values tend to increase.

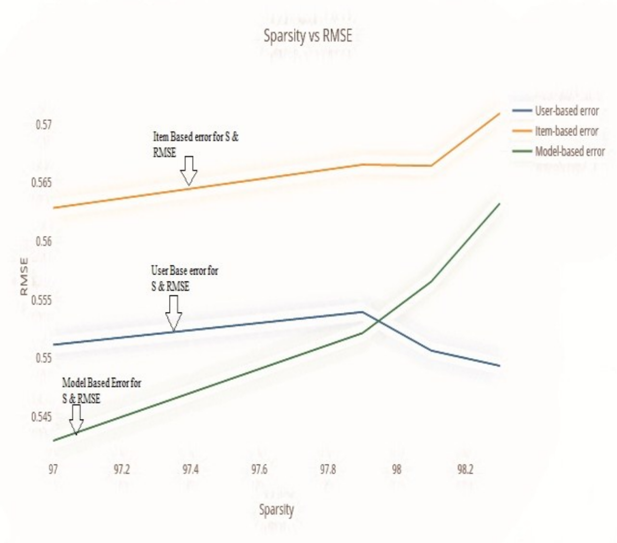

Fig. 2. Sparsity vs. RMSE.

6) User vs. RMSE: The accuracy of predictions with the changing number of users, is represented using RMSE values. The Table III gives the RMSE values for different user numbers.

TABLE III. RMSE VALUES FOR VARYING NUMBER OF USERS

Number of users	*User-based error*	*Item-based error*	*Model-based error*
1000	0.5402	0.5600	0.5442
2000	0.5545	0.5592	0.5392
3000	0.5491	0.5617	0.5406
4000	0.5510	0.5627	0.5418

Figure 3 shows the results for User vs. RMSE. With increase in the number of users sparsity tends to increase so the RMSE values also inflate.

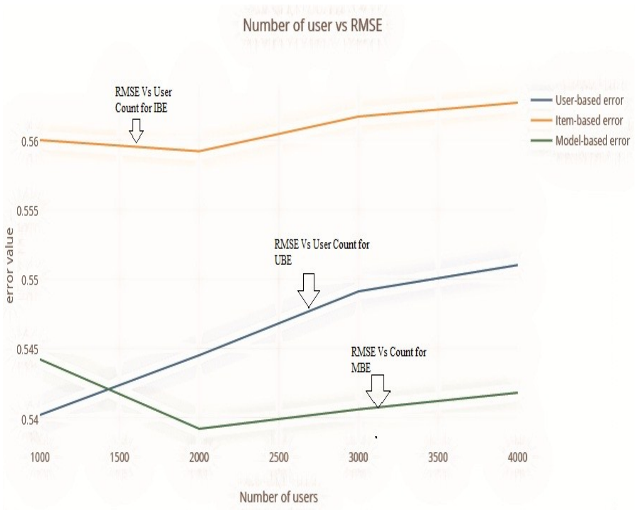

Fig. 3. User vs. RMSE.

7) Item vs. RMSE: The accuracy of predictions with the changing number of items, is represented using RMSE values. The table IV gives the RMSE values for different item numbers.

TABLE IV. RMSE VALUES FOR VARYING NUMBER OF ITEMS

Number of items	*User-based error*	*Item-based error*	*Model-based error*
1000	0.5470	0.5618	0.5360
2000	0.5490	0.5623	0.5410
3000	0.5519	0.5640	0.5435
4000	0.5510	0.5627	0.5418

Figure 4 shows the results for Item vs. RMSE. Similar to user vs. RMSE graph, in this case too sparsity values rise up leading to increase in RMSE.

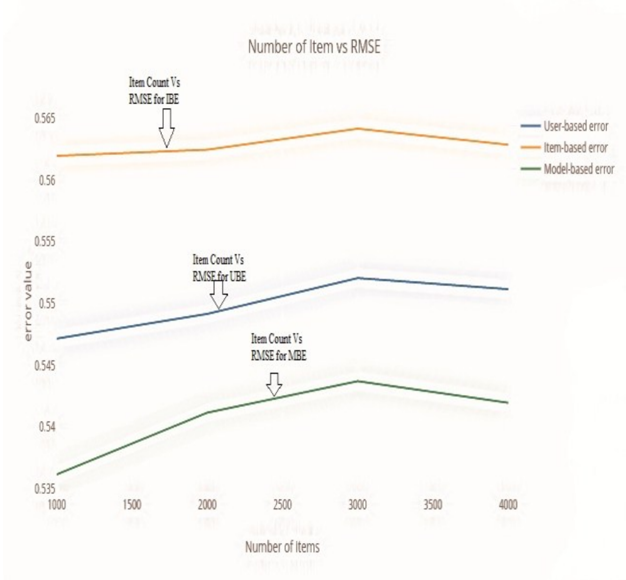

Fig. 4. Item vs. RMSE.

V. CONCLUSION

The prize of 1,000,000 USD was given to Bellkor's pragmatic chaos team who improved the accuracy of existing Netflix's movie recommendation algorithm by 10.06%. The volume of the dataset in e-commerce make the task of making recommendations even more daunting but since customer engagement and satisfaction are at stake it is one of the most sought-after avenues in machine learning nowadays. The collaborative filtering (CF) methods have surely proved to be better than the other conventional methods but the intelligence of the RS is still not at par with the expected standards.

To experience real world scenarios amazon dataset for the transactions made in the year 2012 were taken. It consisted of the details of over 15,00,000 users and over 4,00,000 items. The RMSE error for user-user collaborative filtering was 2.71 while for item-item Collaborative filtering it was 2.62. As the other theories have suggested the error in prediction values for model based Collaborative filtering was the least amounting to a tad over 2.53. The predictions obtained from these algorithms were made available to the users through the web application. With the results and analysis following conclusions are made:

- Model based CF algorithms prove to be better than memory based CF algorithms.
- Error in predictions increase with sparsity of the user-item matrix.

ISBN: 978-988-14048-1-7
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

- Error in predictions may or may not increase with the size of the data set. It actually depends on the user item pair score which is to be appended.

ACKNOWLEDGEMENT

Dr. Anjan K Koundinya would like to thank Late. Dr. V K Ananthashyana, Former Head, Dept. of CSE, MSRIT for igniting passion for research.

REFERENCES

[1] Mahamudul Hasan, Shibbir Ahmed, Md. Ariful Islam Malik and Shabbir Ahmed, "A comprehensive approach towards user-based collaborative filtering recommender system", International Workshop on Computational Intelligence (IWCI), Dhaka, Bangladesh, December 2016, pp. 345-354.

[2] Kangning Wei, Jinghua Huang and Shaohong Fu,"A Survey of E-Commerce Recommender Systems", International Conference on Service Systems and Service Management, Chengdu, China, 2015, pp. 71-77.

[3] Edjalma Queiroz da Silva, Celso G.Camilo-Junior, Luiz Mario L. Pascoal and Thierson C. Rosa, \An evolutionary approach for combining results of recommender systems techniques based on collaborative filtering", International Journal on Expert Systems with Applications, Vol. 53, July 2016, pp. 204-218.

[4] Yingtong Dou, Hao Yang and Xiaolong Deng, "A Survey of Collaborative Filtering Algorithms for Social Recommender Systems", International Journal on Computer Communications, Vol. 41, March 2014, pp. 1-10.

[5] Mohammad Aamir and Mamta Bhusry, "Recommendation System: State of the Art Approach", International Journal of Computer Applications, Vol. 120, No.12, June 2015, pp. 25-32.

[6] Win Win Moe and Nang Aye Aye Htwe, "Performance Comparison of Collaborative Filtering Prediction Methods on Recommendation System", American Scientific Research Journal for Engineering, Technology and Sciences, vol. 28, No 1, 2017, pp.213-221.

[7] Yan Zhang and Yu Li, "A Novel Hybrid Collaborative Filtering Algorithm Research for Music Recommendation", Journal of Multidisciplinary Engineering Science and Technology, Vol. 3, Issue 10, October 2016, pp. 167-178.

[8] Maryam Khanian Najafabadi and Mohd Nazri Mahrin , "A systematic literature review on the state of research and practice of collaborative filtering technique and implicit feedback", Artificial Intelligence Review , An International Science and Engineering Journal, Vol. 45, Issue 2, February 2016, pp. 167-201.

[9] Suyun Wei, Ning Ye and Shuo Zhang, "Item-Based Collaborative Filtering Recommendation Algorithm Combining Item Category with Interestingness Measure", International Conference on Computer Science and Service System, Nanjing, China, August 2012, pp. 134-142.

[10] P. H. Aditya , I. Budi and Q. Munajat, "A comparative analysis of memory-based and model-based collaborative filtering on the implementation of recommender system for E-commerce in Indonesia: A case study PT X", International Conference on Advanced Computer Science and Information Systems ,Bali, Indonesia, October 2016, pp. 234-240.

[11] SongJie Gong, HongWu ye and HendSong Tan, "Combining Memory-Based and Model-Based Collaborative Filtering in Recommender System", Pacific-Asia Conference on Circuits, Communications and Systems, Chengdu, China , May 2009, pp.170-177.

[12] Andrei-Cristian and Prodan, "Implementation of a Recommender System using Collaborative Filtering", Studia Universitatis Babes-Bolyai, Informatica, Vol. 55 Issue 2, 2010, pp. 70-84.

[13] Lalita Sharma and Anju Gera, "A Survey of Recommendation System: Research Challenges", International Journal of Engineering Trends and Technology, Vol. 4 Issue 5, 2013, pp. 1989-1992.

[14] Jie Dong, Yun Qin, Xue Yang Sun and Li Ming Du, \Research on Improved Collaborative Filtering Recommendation Algorithm on MapReduce", International Conference on Mechatronics, Manufacturing and Materials Engineering, Vol. 63, 2016, pp. 203-209.

[15] Mehdi Elahi, Francesco Ricci and Neil Rubens, "A survey of active learning in collaborative filtering recommender systems", An International Journal on Computer Science Review, Vol. 20, May 2016, pp. 29-50.

[16] G. Takacs, I. Pilaszy, B. Nemeth, and D. Tikk, \Scalable collaborative filtering approaches for large recommender systems", Journal of Machine Learning Research, Vol. 10, 2009, pp. 623-656.

[17] V Haifeng Liu, Xiangjie Kong, XiaomeiBai,WeiWang, Teshome Megersa Bekele and Feng Xia, \Context-Based Collaborative Filtering for Citation Recommendation ", International Journal of Engineering and Computer Science, September 2015, pp.222-230.

[18] Shanshan Cao, "A Hybrid Collaborative Filtering recommendation algorithm for Web-based Learning systems", International Conference on Behavioral, Economic and Social-Culture Computing, 2015, pp. 168-171.

[19] R. Burke and M. Ramezani, "Matching recommendation technologies and domains," in Recommender Systems Handbook, Springer, 2011, pp. 367386.

[20] A. Geyer-Schulz, M. Hahsler, and M. Jahn, "Educational and scientific recommender systems: Designing the information channels of the virtual university," International Journal of Engineering Education, Vol. 17, No. 2, 2001, pp. 153-163.

[21] Adomavicius G and Kwon Y, "New recommendation techniques for multicriteria rating systems", IEEE Intelligent Systems, Vol-22 No. 3, 2007, pp. 48-55.

[22] Francois Fouss and Marco Saerens, "Evaluating Performance of recommender systems: An experimental comparison", IEEE International Conference on Web Intelligence and Intelligent Agent Technology, 2008, pp. 67-76.

[23] Amazon India Report in the URL - https://economictimes.indiatimes.com/small-biz/startups/newsbuzz/amazon-is-the-fastest-growing-marketplace-in-india-reiterates-jeff-bezos/articleshow/63824338.cms last visited on 3/7/2018 at 10 :30PM.