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Efficient Feature Selection Method Using Feature Grading for Context-Aware Recommendation Systems

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Abstract: In e-commerce industry, with rapid growth an importance was gained by recommendation system. To suggest products, users feedback was utilized by the recommendation system, that help in accessing the long tail products and also might be useful to the user. To get the correct results from database, it is very necessary to retrieve correct data, it is very big and difficult task to handle these large dataset. In a dataset, feature selection is the automatic attributes selection, which is known as attributes or variable selection, to the predictive modeling problem it is most relevant. Importance of item features makes recommendations more relevant. Therefore, this paper presents Efficient Feature Selection Method Using Feature Grading for Context-Aware Recommendation Systems. In e-commerce business, to make commodities recommendation, a comprehensive algorithm is used which is known as Feature-Grading. Feature-Grading process as follows: Extracting overall feature set commodities of a group category, in the original data, to select and rank the relevant features in binary space, the important features density and weights are considered and finally acquiring feature set based subset of grading set. Root-mean-square-error (RMSE) is the metric for measuring the prediction accuracy. Feature-Grading really works well or not will be revealed by some important results which are discussed by our experimental data.

Keywords: *feature selection, Feature mining, Feature Grading, Recommendation Systems, Sentimental Analysis.*

I. INTRODUCTION

Recommendation systems are gaining increasing popularity in many application areas like e-commerce, movie and music recommendations, tourism, news, advertisement, stock markets, social networks etc. Conventional recommendation systems either use content based or collaborative filtering based approaches to model user preferences and give recommendations. These systems usually fail to consider evolving user preferences in different contextual situations. Context Aware Recommendation Systems take different contextual attributes into consideration and try to capture user preferences correctly. This survey focuses on the state-of-the art computational intelligence techniques trying to improve conventional design using contextual information[1].

People propose the concept of personalized service to present an different content or information to different users. As an important constituent part of the personalized service research field, recommendation systems, through mining the relation between users and items, help users find the items (such as web information, services, online merchandises, etc.), which may be interesting to them from large amounts of items, and generate personalized recommendations to meet users' individual needs[2]. Now, recommendation systems have been widely applied in many application fields, for example, electronic commerce, electronic tourism, internet advertising and so on. In general, a recommendation system use certain technologies and methods to recommend appropriate items to consumers (e.g., movies, books, music, applications, webs and tourist spots) in a personalized way according to their preferences and actual interests. The role of recommendation system is to link isolated users and items, and to establish a dedicated channel for each user to his/her interesting items. In this way, recommendation systems help users find those items which satisfy their personalized requirements, and meanwhile the providers of items leverage recommendation systems push their items to these users who are likely interested in them. Thus, both users and the providers of items can take what they need, to achieve a win-win situation by means of recommendation systems [3].

Compared with a motor enterprise and brick, more options are afforded in the virtual world by an online service. The choosing act can become an overwhelming exercise, when choices are multiplied. With options and choices, every day, people are overwhelmed during surfing web. Where to travel? What to buy? And so on. There are many alternative solutions for each of these questions. Effectively items are recommended with large number of alternatives that users have become an important issues which they are interested in. In terms of watching the movies, listening the songs, online purchase of products in future, to predict the user's interest on the online portals, to capture the user behavior by an intelligent system which is known as recommendation system. Now a days, millions of items are provided by the multiple website to their consumers due to increases the online market popularity. Data can be generated by a recommendation system through the searching pattern, user behavior and past purchase history on the web[4].

To the Ecommerce websites success, the recommender systems are crucial as they streamline the choosing products suited process, from numerous available products to users' interest. Netflix and Amazons recommender systems are included by the successful real-world applications. For example, in the world, one of the largest online retailers is Amazon, to optimize its market growth, robust data-driven analytics has been used with 12.2 million products carried for over 304 million active customers [5]. When customers browse, review products, and buy, to increase sales, product recommendations were provided by the system and based on their history, improve experience of customers. To E-commerce websites, new users that are customers who are potential especially to those of a limited customer base are important. The possibility that purchases of new users increases and can make more effective recommendations, if the new users' preferences was known by the recommender system. Unfortunately, for existing users to get more accurate recommendations, even though more and more methods are put forward, big challenges to new users, the recommending problem was still imposed. The exponential growth in e-commerce industry has provided the users with a wide variety of products to choose from. E-commerce websites are modern day departmental stores with wide range of products[6].

Recommendation systems, a sub-type of information filtering systems, have been actively used to address the information overload problem by highlighting relevant items to the users based on their tastes and previous interaction patterns. As the popularity of recommendation systems kept growing, the number of items available for recommendation also increased. This led to the development of more complex user-item models, which often capture underlying information about users or items to improve the quality of the recommendations and ultimately, the users' satisfaction and engagement. One of the dimensions that was explored as part of this process was context[7].

The stored data was filtered by the recommender filtering system, when the new item or user enter in the online market and to the user likes, the most relevant item was recommended. Based on their working behavior, classified the recommendation system into three main classes. To make effective recommendation, the classes of recommendation systems are Hybrid recommendation system, Content base recommendation system, and Collaborative recommendation system. To generate the recommendation, the items properties are used by the Content based recommendation system based on the previously rated items [8]. In to two different categories, collaborative filtering technique has classified like memory and model based information filtering. To find the unrated items rating, the prediction model was developed by the recommendation CF method.

The CF technique's content-based filtering faces the challenges, to handle, more than one information filtering method was used by the hybrid recommendation technique [9]. Compared to the single technique, the efficient and accurate recommendation was provided by the hybrid filtering technique, which is the idea behind it [10]. For running big data, the distributed computing was designed on a many cluster machines to make computation inexpensive, reliable and fast. The data was split into smaller chunks by a MapReduce job to different partitions and on distributed computing, in a parallel manner job processes as sorting and filtering by a map task [11]. A summary operation was performed by a map task output that became reduce input operation.

For normal web pages, the similar techniques are utilized for commodities by existing search engines which is based on key words matching, meaning that with enough key words, items should be tagged which are saved in the database. However, most of the key words are appended manually by merchants. This mechanism is very low-efficient. Some vital features are easy to neglect. Automatically mine out the key feature items of a group category (i.e. the key words) if there is a system, with less manual operation, to complete the marking process it is possible to improve comprehensive efficiency. Remaining paper is organized as follows: Section II explains Literature survey, Section III presents Described methodology, Section IV describes result analysis and finally paper concludes with Section V.

II. LITERATURE SURVEY

X. Feng and Y. Zeng, et. al. [12] a neural collaborative embedding model (NCEM) of a novel method was proposed. Simultaneously, to capture the word frequency information and global context, a pre-trained BERT model was adopted first, to improve most of the downstream NLP tasks which has been proved. In addition, to learn the each review contribution, a mechanism of self-attention was introduced. Next, a neural standard factorization machine form was developed by stacking multiple layers, which can model second-order and first-order user item interactions. The state-of-the-art recommendation approaches are outperformed by the NCEM, on four public datasets the extensive experiments are shown.

D. -K. Chae, J. A. Shin and S. -W. Kim, et. al. [13] for the accurate recommendation, to exploit both techniques into collaborative filtering task an effective way was explored in this paper, by the deep learning on a wide fields range and huge GAN success are motivated. Collaborative Adversarial Auto Encoders (CAAE) is our proposed recommendation framework, significantly extends the Graph GAN and conventional IRGAN as summarized below: 1) instead of using the MF model, we use auto encoder as our generator, it is one of the most successful deep neural network; 2) as discriminative model, Bayesian personalized ranking (BPR) was employed; and 3) to our framework, another generator model was incorporated that focuses on negative items generating, which items, may not be interested in by a given user. Compared to the conventional GAN-based recommenders, considerably higher recommendation accuracy was not only produced by our proposed framework.

F. Zhu, J. Yang and P. Wang, et. al. [14] from massive features, a Two stage Multi-task Recommendation model (TMRM) was presented which aims to select the important combinations of feature automatically, and through a combination of neural network and tree-based model, to achieve better recommendation it was contributed. On two large sets of public data, extensive experiments on TMRM are conducted, and over state-of-the-art solution on recommendation systems performance, our proposed superiority method was demonstrated the results. L. Uyangoda, S. Ahangama and T. Ranasinghe, et. al. [15] to improve the prediction accuracy with less past records of user, in the recommender system the input parameters are used to optimize the prediction algorithm, via ratings from user-item interaction the user feature relationship scores are derived by applying the proposed approach through authors. Compared to the base collaborative filtering algorithm, by showing 8.4% improvement in the cold problem start, a major drawback in collaborative filtering was addressed. 'MovieLens 100k dataset' is used to carry out the system evaluation and user-feature generation. To other domains generalized the proposed system.

R. E. Vinodhini, R. Archanaa, K. Vimalkumar, and M. V. K. Kiran, et. al. [16] in this paper, a novel was proposed and large number of user reviews are analyzed to rate a product based on its technical specification as a better alternative it serves, from several top e-commerce websites it was dynamically extracted. In this study, specification list was extracted by the proposed approach like camera, processor, battery, etc. and customer reviews from different websites for a product of user specified, and to determine the feature polarity in the review, the crucial terms corresponding to the products technical features are identified and under the specification list it was classified. By aggregating specific score, overall product rate is calculated to individual features. In a product, who target at specific features, for those customers this approach is very useful.

Z. Wu, P. Agyemang, M. Chan, H. Zhou and Y. Xiang, et. al. [17], based on product evolution trends, the user feedback ratings, and image features combination, a new recommendation algorithm was proposed. Using deep neural networks convolution, automatically extracted the image features. Thus, a time-aware visual mode is essentially our technique, over time that represents the different users visual feature preference. Widely adopted online data of Amazon is used to evaluate our model and significantly improvements are shown. K. Dhruv, G. Shashank, K. Vaibhav, et. al. [18] to news recommendation, deep neural networks was applied, focusing on whether users have read given articles and to model the reading order of the projects and users potential characteristics. First, from these hidden factors, over the time, to obtain the user's interest a two-way LSTM is used. As input, the user's behavior data is used to obtain the interest level, used the mechanism of attention, then captured the similarity between the project and the user, and realized finally the news recommendation. Very good results were achieved by this model, and also the cold start was solved.

Z. Ji, M. O'Droma, L. Zhao, and I. Ganchev, et. al. [19] described the `best' mobile services to consumers, which was used to suggest and discover a smart recommendation systems implementation and design. For real-time data scheduling, an efficient computing was provided by a distributed data management platform (DMP) which was built with the Kafka, Hadoop and Strom, and in the cloud, there is a message processing. To actionable analytical datasets, the consumers mobile services' activities are able to turn by the system with the distributed architecture and the `best' mobile services are recommend particularly to each consumer which are applicable under the paradigm of `best served and always best connected ' (S&ABC). In a distributed way, towards this service recommendation system, an approach was running and elaborated high throughput capacity. X. SiMeng and B. JianMin, et. al. [20] method of (Analytic Hierarchy Process)-Based domain recommendation is a new recommendation method which was introduced. With collaborative filtering (CF) algorithm, the user preference model was combined, the recommendation results were generated to construct user preference model by utilizing item domain features. After this, by comparing with other three methods of

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recommendation that including F-MADM, items-based and ratings based, we verify our own method. As we suspect, the best result was achieved by our method as shown in the results.

N. Vahid, S. Philip, Joint, Z. Lei, et al. [21] to express the review text, a pre-trained word embedding technology was used, from the review a semantic information was extracted, and to study the implicit relationship between the commodities feature and the users preferences, content-based recommendation algorithms are combined. Therefore, the implicit feedback can be analyzed effectively by the recommendation system which was combined with deep learning, so with the content-based recommendation algorithm a model was built which is more accurate and comprehensive resulting in the better system performance. J. Lee, M. -U. Kim, and K. Yoon, et. al. [22] human emotions are triggered by the selected low-level musical features, based on the corresponding music and audience rating information on TV music programs. To select the preferred music and to rate the contestants of music based on their emotional feelings are requested by the audience in this program. In addition, personalized music recommendation system was implemented using listed history, context information and selected features. In the music recommendation systems, these features are used when the selected features can be reliable features which are confirmed in the experimental results.

A. Nanopoulos, et. al. [23] in collaborative tagging systems, the item recommendation problem was considered in this paper. With three-mode tensors, from collaborative tagging system a model data was proposed, in order to capture the three-way correlations among items, tags, and users. From a real collaborative tagging system (Last.fm) a data was used against both traditional (non tag aware) and recent tag-aware item, in recommendation quality from experimental comparison a recommendation algorithms indicate.es significant improvements. Moreover, the proposed hybrid scheme advantage was illustrated by the experimental results. M. Bjelica, et. al. [24] under the broadcast scenario, the design of recommender system was analyzed, to the network center the uplink connection is not available. The user’s interests would be able to efficiently learn by the user modeling algorithm, on which we kept the special emphasis. Information retrieval theory, like cluster hypothesis and vector spaces, as well as pattern recognition and machine learning elements are applied by our proposal. The proposed recommendations high acceptance ratio was shown by the experimental results which is computationally simple is known as derived algorithm.

III. EFFICIENT FEATURE SELECTION METHOD USING FEATURE GRADING

The block diagram of Efficient Feature Selection Method Using Feature Grading for Context-Aware Recommendation Systems is represented in below Fig. 1. From Amazon, we took the advantageous of multi-band mobiles information. In the database, reviews and titles are stored. Stopword and tokenization are the techniques of natural processing language which is used to pre-process raw review text. For further analysis, the review text was broken into separate terms by the referred tokenization which is called as tokens, which can be treated as individual identity. Just to obtain the terms, by the stopword removal, the tokenization is followed that discards the redundant terms and contain useful user feedbacks insights.

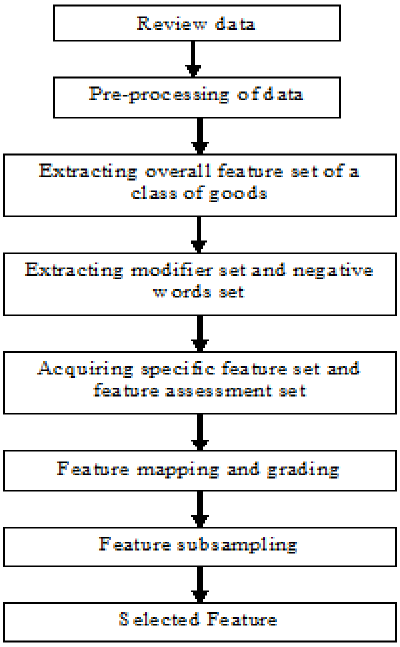

Fig. 1: Block Diagram of Efficient Feature Selection Method

With a subsetting method, we came up with crucial voluminous which is known as real datasets, for feature training selection that only takes a small data fraction to use all the data, a comparable result was given. Among users, sessions distribution was preserved in a way that we subset the input data. First, to split each review into independent words, we use the ICTCLAS (Chinese Lexical Analysis System, Institute of Computing Technology) with the tags of speech part. We can obtain tagging results and satisfied splitting with further optimizing. From these separate words, now we need to extract typical features after getting the desired review. With “/n”, tagged always nouns which are known as features, according to the habits of Chinese expression. Firstly, we came up with the Association Mining

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idea, typically, to identify feature an Apriori algorithm is used. In the reviews, frequently appearing associated words by mining that was achieved. Associated words are involved, once, a comment on an item was made by a customer, then this is the reason to use it. With Apriori Algorithm, the whole reviews are handled, when appropriate feature set was eventually acquired. Category of eventually satisfied feature sets commodities are indicated as N=$\{N_1, N_2, \ldots, N_m\}$, where, the number of total features is *m*.

In reviews, the modifiers have to recognize firstly for the analysis and their orientation must be judged. With "/v" and "/a", the words tagged always by the modifiers in the splitted reviews. Here, polarized modifiers are only considered, namely those can be negative or positive. To identify its orientation and a modifier, in Word-Net, the modifier synonym group is involved, a effective and simple way has utilized. By hand some qualified modifiers are initially picked up as seeds and with ±1 label, they were marked. Through such synonym, the original modifiers orientation can be judged once a seed turned from synonym. Negative words need to extract, to final sentimental identification they contributed. With "/d", always tagged the negative words. Neg indicates the negative word set. Through their reviews, we are able to acquire the each individual items feature of specific set, after obtaining a whole categories feature set of N commodities. As F = $\{F_1, F_2, \ldots, F_k\}$, indicated the specific feature set, where an item owns the number of known features is known as *k*. In fact, features of uncommented are unknown to us, an items all the features cannot be covered by the reviews in database and to decide them subjectively, we do not have right. Therefore, as they don't have unknown features in database, can be considered only items. Obviously, F is a subset of N and different item has different F.

Relationship between the encoded binary features and the original feature space are recorded by the map which we have saved. Suppose, in set F, there are rl indices appearing, then there are tl = rl/dl indices fraction of feature l that are important. Following two lists are generated:

1) For each context feature, in the binary vector a list of indices number is selected: r = [r3, ⋯ , rm];

2) For each context feature, in the binary vector a list of indices fraction is selected: t = [t3, ⋯ , tm].

By simply ranking t & r, the graded lists t and r are merged, which is the t and r element-wise multiplication. For grading, a to grade individually each feature is a direct idea for an item and marked as its final, the sum has to be find. The feature is more appreciated which was meant to be more positive reviews for the ith items jth feature. In the original feature space, a features grading was given to us. For prediction error affecting, we want to account the grading which leading the most important features not to select. Suppose we want to choose p features. In this case, from the garded feature list we first choose top significant features of q = 2p ∼ 4p << (m − 2), from these q features, p features are sub-sampled uniformly. With domain knowledge, selected features can be improved optionally, it may be noted that, although features can be selected automatically by the framework. For each of these selected feature sets, we actually train the model and with the best results we choose the set. After feature grading, our framework may also be adapted to decide automatically to select the number of context features, important features are chosen from the top of the graded/ranked list.

IV. RESULT ANALYSIS

After the comprehensive recommendation algorithm design, from Amazon, multi-band mobiles information took advantages. In the database, their reviews and titles are stored. In our proposed model, in life, some major processes are tested on these real data basis. Feature set extractions experimental results were shown in table I.

Fig. 1: Extracted Feature Set Results

Item	Number
Review set	14100
Overall features	91
Negative features	37
Graded features	78
Final feature set	66

Under the worst situation, our approach has a t * m time complexity, where the number of items was referred to as t and the number of overall features was referred to as m. However, under the worst situation whose complexity can be $t^2 * p$ is the existing models, who bought the item is the number of customers known as p. Compared to the existing ones, our methods has much less time complexity which was revealed by comparison. The performance of described model is evaluated through performance parameters as Root-Mean-Square Error (RMSE) and time consumption for content aware recommendation system.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \ldots\ldots(1)$$

Where, i-th sessions session progress is known as y_i , the i-th sessions predicted session progress is known as $\hat{y}_i$, the total number of sessions is known as n.

To find a model is our objective, on test set that has the smallest RMSE, and for feature selection, to select a small context features subset is our goal for training, ensuring that any context features are not using at all or compared to using all context features, the RMSE is better, and a human expert selected comparable to the features set. First, over different runs we test our framework. Comparison of RMSE values for total feature set, human generated feature set and final feature set of described model in below table 2.

Table 2: Performance Comparison

Type of Feature sets	RMSE
Total feature set	0.4
Human generated	0.3
Final feature set of graded model	0.18

Fig. 2 shows the graphical representation of RMSE value of different feature sets. Fig. 3 shows the time required for recommendation system with human generated feature set and described Final feature set of graded model.

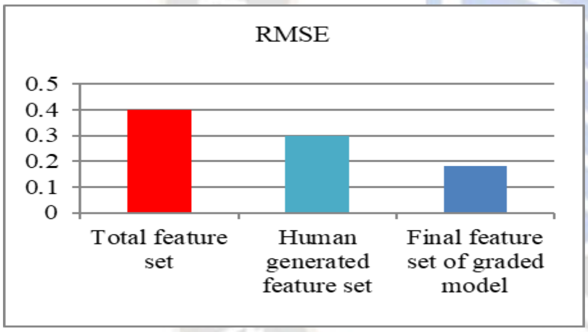

Fig. 2: Performance Comparison In Terms Of RMSE

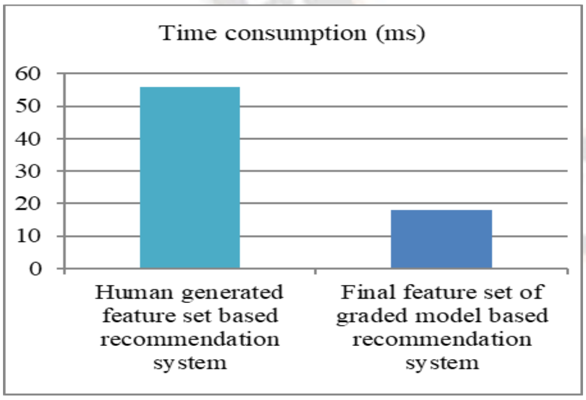

Fig. 3: Performance Comparison In Terms Of Time Consumption

It is observed that, least RMSE is obtained for Efficient Feature Selection Method Using Feature Grading. Therefore, from results it is clear that, efficient feature set extraction is required for construct a content based recommendation system.

V. CONCLUSION

In this paper, Efficient Feature Selection Method Using Feature Grading for Context-Aware Recommendation Systems is described. To suggest products, user feedback was utilized by the recommended system, to the user that might be useful and in accessing the long tail products it helps. The large data of review set can be handled by selecting the features. From Amazon, multi-band mobiles information was collected. We select the feature set for original review data. Through their reviews, we are able to acquire each individual items specific feature set, after obtaining the whole category feature set N commodities. Grading technology is used to select the features. For grading, individually to grade each feature is a direct idea for an item and marked it as final, the sum should be find. The performance of described model is evaluated through performance parameters as Root-Mean-Square Error (RMSE) and time consumption for content aware recommendation system. least RMSE is obtained for Efficient Feature Selection Method Using Feature Grading. Therefore, from results it is clear that, efficient feature set extraction is required for constructing a content based recommendation system.

REFERENCES

[1] V. A. Patil and D. J. Jayaswal, "Capturing Contextual Influence in Context Aware Recommender Systems," *2019 International Conference on Data Science and Engineering (ICDSE)*, Patna, India, 2019, pp. 96-102, doi: 10.1109/ICDSE47409.2019.8971789.

[2] S. Yang, K. Zhu and W. Liang, "Differential Privacy for Context-Aware Recommender Systems," *2019 IEEE 18th International Conference on Cognitive Informatics & Cognitive Computing (ICCI*CC)*, Milan, Italy, 2019, pp. 356-360, doi: 10.1109/ICCICC46617.2019.9146057.

[3] Z. Zhang *et al*., "A context-aware recommendation system based on latent factor model," *2017 13th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD)*, Guilin, China, 2017, pp. 1-6, doi: 10.1109/FSKD.2017.8392858.

[4] Q. Wu, P. Zhao and Z. Cui, "Visual and Textual Jointly Enhanced Interpretable Fashion Recommendation," in IEEE Access, vol. 8, pp. 68736-68746, 2020, doi: 10.1109/ACCESS.2020.2978272.

[5] C. -D. Wang, Z. -H. Deng, J. -H. Lai and P. S. Yu, "Serendipitous Recommendation in E-Commerce Using Innovator-Based Collaborative Filtering," in IEEE Transactions on Cybernetics, vol. 49, no. 7,

pp. 2678-2692, July 2019, doi: 10.1109/TCYB.2018.2841924.

[6] H. Xu, K. Li and G. Fan, "Novel Model of E-Commerce Marketing Based on Big Data Analysis and Processing," *2017 International Conference on Computer Network, Electronic and Automation (ICCNEA)*, Xi'an, China, 2017, pp. 80-84, doi: 10.1109/ICCNEA.2017.51.

[7] C. Morgan, I. Paun and N. Ntarmos, "Exploring Contextual Paradigms in Context-Aware Recommendations," *2020 IEEE International Conference on Big Data (Big Data)*, Atlanta, GA, USA, 2020, pp. 3079-3084, doi: 10.1109/BigData50022.2020.9377964.

[8] F. Ullah, B. Zhang and R. U. Khan, "Image-Based Service Recommendation System: A JPEG-Coefficient RFs Approach," in IEEE Access, vol. 8, pp. 3308-3318, 2020, doi: 10.1109/ACCESS.2019.2962315.

[9] C. -Y. Lin, L. -C. Wang and K. -H. Tsai, "Hybrid Real-Time Matrix Factorization for Implicit Feedback Recommendation Systems," in IEEE Access, vol. 6, pp. 21369-21380, 2018, doi: 10.1109/ACCESS.2018.2819428.

[10] S. Wan and Z. Niu, "A Hybrid E-Learning Recommendation Approach Based on Learners' Influence Propagation," in IEEE Transactions on Knowledge and Data Engineering, vol. 32, no. 5, pp. 827-840, 1 May 2020, doi: 10.1109/TKDE.2019.2895033.

[11] S. G. K. Patro *et al.*, "A Hybrid Action-Related K-Nearest Neighbour (HAR-KNN) Approach for Recommendation Systems," in IEEE Access, vol. 8, pp. 90978-90991, 2020, doi: 10.1109/ACCESS.2020.2994056.

[12] X. Feng and Y. Zeng, "Neural Collaborative Embedding From Reviews for Recommendation," in IEEE Access, vol. 7, pp. 103263-103274, 2019, doi: 10.1109/ACCESS.2019.2931357.

[13] D. -K. Chae, J. A. Shin and S. -W. Kim, "Collaborative Adversarial Autoencoders: An Effective Collaborative Filtering Model Under the GAN Framework," in IEEE Access, vol. 7, pp. 37650-37663, 2019, doi: 10.1109/ACCESS.2019.2905876.

[14] F. Zhu, J. Yang and P. Wang, "TMRM: Two-Stage Multi-Task Recommendation Model Boosted Feature Selection," 2019 IEEE 31st International Conference on Tools with Artificial Intelligence (ICTAI), Portland, OR, USA, 2019, pp. 1277-1281, doi: 10.1109/ICTAI.2019.00-89.

[15] L. Uyangoda, S. Ahangama and T. Ranasinghe, "User Profile Feature-Based Approach to Address the Cold Start Problem in Collaborative Filtering for Personalized Movie Recommendation," 2018 Thirteenth International Conference on Digital Information Management (ICDIM), Berlin, Germany, 2018, pp. 24-28, doi: 10.1109/ICDIM.2018.8847002.

[16] M. V. K. Kiran, R. E. Vinodhini, R. Archanaa and K. Vimalkumar, "User specific product recommendation and rating system by performing sentiment analysis on product reviews," 2017 4th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2017, pp. 1-5, doi: 10.1109/ICACCS.2017.8014640.

[17] Z. Wu, P. Agyemang, M. Chan, H. Zhou and Y. Xiang, "Improved one-class collaborative filtering for online recommendation," 2017 International Workshop on Complex Systems and Networks (IWCSN), Doha, Qatar, 2017, pp. 205-209, doi: 10.1109/IWCSN.2017.8276528.

[18] K. Vaibhav, K. Dhruv, G. Shashank, "Deep Neural Architecture for News Recommendation", in Working Notes of the 8th International Conference of the CLEF Initiative. Pp.142-162, 2017

[19] I. Ganchev, Z. Ji, M. O'Droma and L. Zhao, "Smart recommendation of mobile services to consumers," in IEEE Transactions on Consumer Electronics, vol. 63, no. 4, pp. 499-508, November 2017, doi: 10.1109/TCE.2017.015115.

[20] B. JianMin and X. SiMeng, "AHP-based domain features recommendation method," 2017 IEEE 3rd Information Technology and Mechatronics Engineering Conference (ITOEC), Chongqing, China, 2017, pp. 768-772, doi: 10.1109/ITOEC.2017.8122455.

[21] Z. Lei, N. Vahid, S. Philip, Joint. "Deep Modeling of Users and Items Using Reviews for Recommendation", Proceedings of the Tenth ACM International Conference on Web Search and Data Mining. Pp. 425-434, 2016

[22] K. Yoon, J. Lee and M. -U. Kim, "Music recommendation system using emotion triggering low-level features," in IEEE Transactions on Consumer Electronics, vol. 58, no. 2, pp. 612-618, May 2012, doi: 10.1109/TCE.2012.6227467.

[23] A. Nanopoulos, "Item Recommendation in Collaborative Tagging Systems," in IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, vol. 41, no. 4, pp. 760-771, July 2011, doi: 10.1109/TSMCA.2011.2132708.

[24] M. Bjelica, "Towards TV recommender system: experiments with user modeling," in IEEE Transactions on Consumer Electronics, vol. 56, no. 3, pp. 1763-1769, Aug. 2010, doi: 10.1109/TCE.2010.5606323.