TEST Engineering & Management

November-December 2019
ISSN: 0193-4120 Page No. 6585 - 6591

Improving the QoS of Recommender Systems using Adaptive Machine Learning

Mukul M. Bhonde[1]* Dr.Pramod N. Mulkalwar[2]

[1]*Assistant Professor,ShriShivaji Science College, Amravati,Maharashtra, India*
email: mukul15@gmail.com
[2]*Associate Professor, AmolakchandMahavidyalaya, Yavatmal, Maharashtra, India*
e-mail: pnm_amv@rediffmail.com

Article Info
Volume 81
Page Number: 6585 - 6591
Publication Issue:
November-December 2019

Article History
Article Received:*5 March 2019*
Revised: *18 May 2019*
Accepted: *24 September 2019*
Publication: *31 December 2019*

Abstract:
Recommendation based systems have gained a lot of popularity due to their wide range of applicability. From e-commerce-based product recommendation, to social media-based friend recommendation, these systems can be used for any kind of pattern analysis targeted to recommending data based on interlinked usage statistics. In order to improve the quality of such systems, they must have a strong pattern recognition engine, combined with a strong prediction engine. Because, a strong pattern recognition engine will be able to analyze and distinguish different patterns effectively, and the prediction engine will be able to merge these patterns together in order to predict the recommendation for the system. Generally, algorithms like neural network, k-means, kNN and SVM based pattern analyzers are combined with neighborhood-based, context-aware pattern analysis-based and collaborative filtering-based predictors in order to develop a complete recommendation system. Many authors have also combined recommender systems in order to generate a high-performance hybrid recommender. In this paper we have proposed a machine learning based recommender system which uses strengths of different recommender systems in order to improve the overall recommendation accuracy. Furthermore, the performance is compared with some state-of-the art systems in order to evaluate the performance of the proposed system

Keywords:*Recommender, machine learning , pattern, prediction, collaborative, context, content*

I. Introduction

Recommending items of interest based on usage patterns is tremendously driving social and ecommerce website revenues. This is possible due to the presence of highly interconnected social and ecommerce information that is provided by users free-of-cost via their personal logins on these websites. All this information is represented in the form of interconnected data graphs, which tend to extend from few thousand connections to more than 10 million connections, based on the application under study. But processing such complex data graphs requires implementation of algorithms which can; not only analyse the data patterns but also predict next data patterns with utmost accuracy. Recommender systems use the following steps while performing recommendation tasks for any system-under-test,

- Cross-domain data acquisition and pre-processing

This is one of the crucial steps in recommendation. In this step, the data from different sources is collected, and pre-processed in order to remove any duplicates, missing values or redundancies. The data collection process has to be done accurately, because based on the collected data, the system will be able to predict patterns and finally recommend items which are either most-frequently used, or items which need most attention (like a product on an ecommerce website which is not moving due to people tweeting incorrectly about it). Moreover, this step is also

TEST Engineering & Management
November-December 2019
ISSN: 0193-4120 Page No. 6585 - 6591

decided by the application under test, and decides the overall performance of the system.

- Data linking and processing for recommendation

Data collected from different sources needs linking with the help of certain keys. For example, social media data about users can be linked with the user's buying patterns from the ecommerce data via the user's unique ID. This process of linking fuses the data from different sources into a single dataset, and makes it easier for processing.

- Pattern analysis and classification

The fused data is given to a pattern analyser, wherein the data is either clustered into different groups, and similarity between data patterns is evaluated, or the data is used for classification of any new input entry. In either case, patterns obtained from the input dataset are used for developing a trained engine which is used for recommendation.

- Recommendation based on classified data

The trained engine developed during the pattern analysis phase is given a set of inputs. These inputs are processed by the engine, and an output recommendation is obtained. This recommendation is often found in terms of most probable product which you might buy on ecommerce websites, or most probable user which can be your friend on social media. The output of this step decides the accuracy and effectiveness of the system under test.

- Post-processing tasks

Once the recommendations are made, then the system might need re-tuning, or the recommended data might be used as an incremental learning entry for the trained system. These post-processing tasks are evaluated in this step, and are not always required for recommendation systems.

Based on the given steps, researchers have developed different techniques for recommendation. A sample recommendation system which recommends movies based on social data is shown in the following figure, where in because the users are friends, and their movie patterns match, so the movie seen by one user is recommended to her friend.

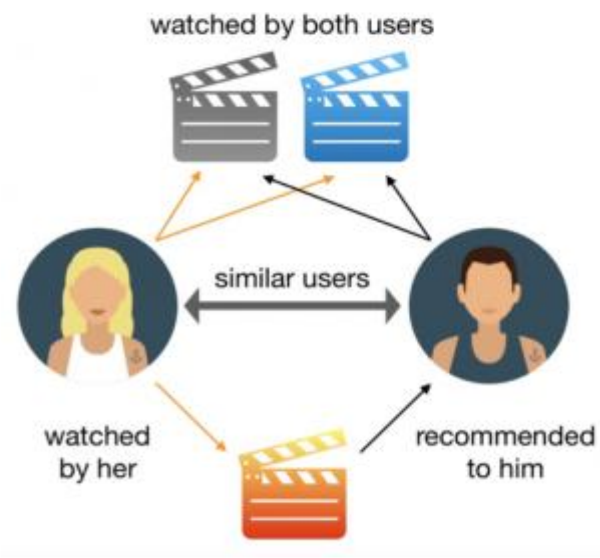

Figure 1. Social relationship-based movie recommender

The next section does a deep-dive into these techniques, and allows for the readers to analyse which techniques can be used for what kind of application. In the later section, we discuss the proposed machine learning algorithm, and its performance analysis. We later conclude this paper with some interesting observations about the proposed algorithm, and ways to improve it.

II. Literature Survey

Recommendation frameworks have made some amazing progress, from basic limit-based recommenders to profoundly complex profound learning-based recommenders. Straightforward recommenders give balanced proposals, such as prescribing what to purchase and what not to purchase dependent on a specific attribute of an item. In any case, as multifaceted nature builds, the recommenders can anticipate the clients' purchasing behaviors, and suggest things like, what the client can purchase dependent on a mix of past buy accounts of the client and their companions. Also, this framework turns out to be computationally costly, and the proposal cost-to-yield proportion increments. Different procedures [1] have been referenced so as to improve the proposal, and diminish the expense to-yield proportion. Most broadly utilized strategies for proposal incorporate, Collaborative Filtering, Content-Based and Hybrid methodologies. These methodologies ensure that the general proposal process is compelling and that the productivity of suggestion is improved. Cooperative sifting [1] utilizes information from various sources so as to prescribe a thing to the client. This information can be in the structure evaluations, or surveys, or whatever other metric which is helpful to depict the thing under proposal. Cooperative sifting approaches incorporate Memory based User to User (MBU2U), Memory based Item to

November-December 2019
ISSN: 0193-4120 Page No. 6585 - 6591

Item (MBI2I), Model Based Clustering (MoC), Model based Matrix Factorization (MoMF). The MBU2U approach utilizes client likeness for proposal, while MBI2I utilizes thing based similitude so as to suggest elements of intrigue. Both the models are vigorously reliant on solid dataset reliance. On the off chance that the accessible datasets have great interconnections, at that point the calculation will have the option to discover the associations between clients or things, so as to exhibit solid proposals. Interestingly, the MoC utilizes grouping approaches so as to make forecasts. The created grouping model will empower information purposes of comparable highlights to be clubbed together, and along these lines helping with recognizing information designs which are like one another. The MoMF model is better than the various models, and it uses the data gave by all the various models so as to produce a suggestion motor that can anticipate client conduct, and along these lines improving the thing proposal for the client.

Another sort of proposal process is called as substance-based suggestion. It utilizes either thing based or client profile-based proposal, and uses diverse sort of similitude measurements like cosine, jaccard, pearson, balanced cosine, obliged relationship, mean squared contrasts and outline coefficient. Every one of these measurements [1] discover the likeness of the client under test with the other clients' profiles, and dependent on this closeness proposals are made. A top to bottom investigation of these methods is referenced in [1]. Prescribing items on web-based business sites covers over 30% of a wide range of suggestions. The examination done in [2] thinks about the work done by different scientists in the area of enormous information based online business suggestions. There is no measurable examination done by the creators, yet the work gives a concise thought regarding the ideas utilized while structuring recommenders for enormous information frameworks.

Space explicit recommenders give preferred exactness over universally useful recommenders. The framework proposed in [3] utilizes level of view as a measurement for suggestion of films to clients. Their recommender depends on inputs given by clients in the wake of watching motion pictures. These criticisms are then collected into a level of view metric, lastly suggestion is finished. In view of their examination, the Content-based Linear Regression, Content-based Random Forest, Collaborative Model-based, Collaborative User-based and Collaborative Item-based methodologies are sub-par when contrasted with the proposed calculation. The mistake level of the proposed calculation is diminished by 3% when contrasted with these strategies. While utilizing measurable measurements prepares for proposal, a few analysts like Bushra Alhijawi [4] and others utilize semantic data so as to make suggestion frameworks. The work done in [4] utilizes communitarian sifting and consolidates semantic importance of things so as to perform proposal. The framework uses rating information for a specific thing, and joins it with semantic criticism about the thing so as to assess the position of the thing. In view of this position, the thing is prescribed to the clients. The acquired outcomes feature that score standardization works better, and can diminish the blunder by over 20% when contrasted with non-standardized methods like Pearson similitude, Pearson relationship cosine likeness. The proposed method is additionally contrasted and its own non-standardized rendition, and it is discovered that standardization improves the exactness of the proposed strategy by 10%.

Another motion picture suggestion framework like [3] is proposed in [5]. In the framework, the creators have utilized shared separating so as to prescribe motion pictures to clients. They have utilized User Neighborhood for client based proposal and Log Likelihood Similarity for thing based suggestion so as to build up a half breed recommender. The paper depicts an intriguing methodology for proposal, yet doesn't give any factual investigation to the equivalent. The methodology must be returned to before genuine execution. Half and half recommender frameworks are the eventual fate of suggestion frameworks, and when joined with AI, they further will in general give profoundly precise outcomes. This has been demonstrated by the exploration done in [6], wherein AI is utilized for proposal frameworks. The scientists have assessed the exactnesses of Supervised learning, Unsupervised learning, Semi-administered learning and Reinforcement learning. The outcomes grandstand that support learning joined with huge information can give high exactness, and least mistake when contrasted with different frameworks.

Having an enormous dataset doesn't generally ensure high exactness. So as to accomplish high exactness, the framework engineer must have the option to recognize highlights which are variation enough, that after utilizing them the framework will have the option to recognize various arrangements of information successfully, and will have the option to order data effectively. A strategy to recognize such variation data is characterized in [7], wherein a community oriented separating - based suggestion calculation utilizes bunching and dimensionality decrease so as to get a high precise recommender. The calculation utilizes k-Means joined with solitary worth deterioration (SVD) so as to improve the suggestion exactness. The framework is contrasted and kNN and straightforward k-Means based framework so as to demonstrate that the root mean squared mistake (RMSE) of the proposed calculation is decreased by over

November-December 2019
ISSN: 0193-4120 Page No. 6585 - 6591

10% when contrasted with different strategies. As recently proposed, that semantic data can be helpful for suggestion. The work in [8] utilizes word2vec, which is an opinion investigation instrument, so as to change over the information audits into scores, and afterward dependent on these scores a bunching calculation is contrived so as to perform proposal. The blunder of the proposed calculation is 20% lower than that of the ICRRS [8] strategy. It is prescribed to additionally assess the presentation of this technique on various datasets, and contrast it and various calculations so as to remark on its ease of use.

AI calculations can lessen the mistake of proposal to an exceptionally low level. This can be seen from the work proposed in [9], wherein the specialists have utilized the Mahout Apache system so as to execute client inclination based suggestions. The general mistake is decreased to under 10%, and along these lines the framework can precisely suggest elements. A study of such AI and profound learning procedures is given in [10], wherein it is reasoned that profound learning and AI based recommenders can be valuable for social suggestions, web-based business proposals, motion picture suggestions, and so forth and can perform at exceptionally high correctness's.

An alternate methodology towards suggestion of books in the event of a mutual record structure is given in [11]. Here, analysts have utilized a COVER calculation for thing-based disambiguation. The COVER calculation improves the presentation of top-K rules calculation, and diminishes the blunder rate utilizing disambiguation. The calculation can improve the exactness by practically 10%, when contrasted with top-K rules calculation, and in this way can be utilized in straightforward proposal structures. The calculation's exhibition isn't assessed for complex cross-space issues, and along these lines that territory must be investigated by intrigued perusers. Fuse of COVER with profound learning can be suggested, because of the characteristic focal points of profound learning frameworks. A portion of the favorable circumstances are referenced in [12]. The work in [12] utilizes a profound conviction organize (DBN) so as to improve the suggestion precision of Movie Lens dataset. The outcomes are contrasted and Hybrid Features Selection Algorithm (CHFSA), and it is discovered that the proposed calculation decreases the mean total mistake by over 10%. The calculation can think about both semantic and non-semantic qualities, and consequently should be utilized as a proposal framework for any sort of dataset.

Setting mindful proposal frameworks contemplate the setting of the client under which suggestions are required. The work done in [13], proposes Declarative Context-Aware Recommender System (D-CARS) that makes client explicit profiles by thinking about the client's verifiable utilization information. They likewise propose the utilization of User Window Non-Negative Matrix Factorization point model (UWNMF) for profile age, and Subspace Ensemble Tree Model (SETM) for examination of information given by different clients. The proposed strategy is contrasted and CTT, SVD, and NMF models, and it is assessed that the blunder execution of the proposed algorithm. Various other algorithms [14-16] also prove that using machine learning-based models [17-19] improve the overall efficiency of the recommendation system [20]. In the next section we describe the proposed machine learning-based recommendation system, followed by the performance analysis of the same.

III. Proposed machine learning-based recommendation model

The proposed recommendation model works using 2 phases. The first phase performs intensive learning, while the second phase performs incremental learning with evaluation. The proposed two step machine learning algorithm for recommendation can be described as follows,

Pre-execution phase

In the pre-execution phase, the system performs static recommendation purely based on the input patterns, and therefore it should be run only once for the entire recommendation process.

Initialize machine learning parameters
Number of solutions is represented as Ns
Number of learning iterations is represented as Ni
Learning Rate is represented as LR
Number of recommenders to be used is represented as N
Minimum number of recommenders for each solution as Nmin
Maximum number of recommenders for each solution as Nmax
Pre-step: -
Mark all solutions need to be changed in the current round
Step I: -
Go to each iteration from 1 to Ni
Go to each solution from 1 to Ns
If the solution is needed to be changed, then
Find a random number between (Nmin to Nmax) = Nsol
Select random Nsol numbered recommender units from the total list of recommender units
Give the input dataset to each of the recommender units and find the learning factor (lf)

November-December 2019
ISSN: 0193-4120 Page No. 6585 - 6591

lf = Number of correct recommendations / Total number of recommendations … (1)

Step II:-

Find the mean learning factor (MLf) as

$MLf = \sum lf_i / NS$ … (4)

Find learning factor threshold (THlf) as,

$THlf = Mlf \times LR$ … (5)

Step III:-

If $lf_i < THlf$

Solution is needed to be changed in next round

Else

Solution can be kept as it is for next round

Step IV:-

Mark the solutions which are needed to be changed, and pass them to Step I, and repeat it for Nr rounds

Step V:-

Select the solution with maximum learning factor or maximum efficiency with respect to recommendation

Step VI:-

Create a machine learning look up table, which contains the following entries,

Number of selected recommenders	Selected recommender names	Recommender outputs	Learning factor

Table 1. The table from the pre-execution phase

Execution phase

- Once the pre-execution phase is done, and the system is performing recommendation; the value of learning factor is evaluated after successful completion of 'k' execution cycles.
- In this case, 'k' is the algorithm's complexity factor, and can be in the range of [1-N], where N the max number of recommendations which can be produced.
- Once the value of learning factor (LF) is evaluated, then it is compared with the table 1
- If the value of LF is higher than any entry, then the table is revisited, and the recommender configuration is changed accordingly
- The current value of LF is updated in the table, and the process is repeated

All recommendations are produced using this algorithm, and due to its simplicity of execution, the time needed for evaluation of recommendations is minimum, thereby the response time of the algorithm is minimized. This allows the system to have maximum speed, with better QoS than the existing non-machine learning based systems. We evaluated the performance of the proposed algorithm and compared it with existing ML algorithms. The results for the same are described in the next section.

IV. Result and Analysis

We evaluated the system using cross-domain recommendation, wherein data from Amazon and Facebook was taken in real-time. This data was cross-referenced using the friend ID, and based on this cross-referencing recommendation were made. The parameters used for recommendation can be described as follows,

Parameter Name	Platform	Usage
User ID	Amazon	The ID of the user on ecommerce
Friend ID	Facebook	The corresponding friend ID of the same user on social media
Rating	Amazon	Rating for a product
Product ID	Amazon	Product which is under review
Friend IDS	Facebook	IDs of other friends of this user
Age & Relevance	Facebook	Age and relevance of these users on social media

Table 2. Dataset information

Based on this dataset, we used different state-of-the-art recommendation algorithms like Collaborative filtering, context-based recommender, content-based recommender, k-Nearest neighbor recommender and Term frequency & Inverse document frequency-based recommenders. These recommenders allowed us to compare the performance of the proposed algorithm in terms of the following parameters,

Accuracy = (TP+TN)/(TP+FP+FN+TN)
Precision = TP/(TP+FP)
Recall = TP/(TP+FN)
F1 Score = 2(Recall * Precision) / (Recall + Precision)*

where, TP = Total number of results which must be recommended and are present at the output

TN = Total number of results which must not be recommended and are not present at the output

FP = Total number of results which must not be recommended and are present at the output

FN = Total number of results which must be recommended and are not present at the output

Using these equations, we evaluated the parameters and obtained the following results for precision of the algorithms,

November-December 2019
ISSN: 0193-4120 Page No. 6585 - 6591

Number of recommendations	Collaborative Filtering	Context Aware DCW	kNN	Tf IDF Based	Proposed Model
5	87.5	90	90	91.1	98.6
10	87.6	91.2	90.5	90.4	99.16
15	87.65	91.5	90.56	90.7	99.2
20	87.73	91.9	90.8	90.95	99.3
25	87.81	92.6	90.91	91.2	99.5
40	88.3	92.8	91.19	91.3	99.8
50	89.5	92.6	91.4	91.5	99.1
75	89.9	92.9	91.61	91.7	99.7
100	90.2	93.3	91.83	91.9	99.8

Table 3. Results of precision for different algorithms

Similar results were obtained for the recall values,

Number of recommendations	Collaborative Filtering	Context Aware DCW	kNN	Tf IDF Based	Proposed Model
5	82.6	85.6	91.2	93.5	97.9
10	82.9	85.7	91.3	93.6	97.91
15	83.1	85.9	91.5	93.6	97.95
20	83.2	86.2	91.7	93.67	97.97
25	83.45	86.35	91.85	93.72	98
40	83.65	86.55	92.02	93.77	98.02
50	83.85	86.75	92.19	93.82	98.05
75	84.05	86.95	92.36	93.87	98.07
100	84.25	87.15	92.53	93.92	98.1

Table 2. Recall values

Due to an increase in precision and recall values, the values for accuracy also improved drastically when compared to the existing algorithms. This can be observed using the following table.

Number of recommendations	Collaborative Filtering	Context Aware DCW	kNN	Tf IDF Based	Proposed Model
5	95.1	95.6	93.2	94.3	98.6
10	95.2	95.7	93	94.6	98.7
15	95.25	95.8	93.3	94.7	98.96
20	95.27	95.91	93	94.93	99.12
25	95.35	96.2	93.4	95.13	99.3
40	95.4	96.27	93.3	95.33	99.36
50	95.46	96.41	93.34	95.53	99.38
75	95.51	96.55	93.38	95.73	99.39
100	95.57	96.69	93.42	95.93	99.4

Table 3. Comparison of accuracy for different algorithms

From the accuracy table, we can observe that the overall accuracy has been improved by more than 8%ile, which is a very big improvement. This improvement is due to the inclusion of different state-of-the-art algorithms in the learning paradigm of the algorithm. The following graph assists in the evaluation of the accuracy comparison,

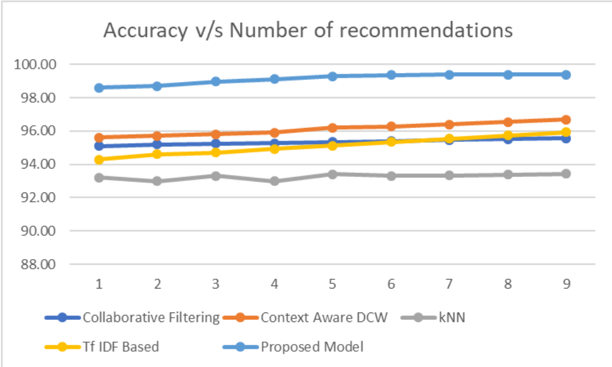

Figure 1. Accuracy comparison

Due to this improvement in accuracy, the system can be used for any kind of real-time recommendations. The overall delay of recommendation is also very low when compared to the other algorithms. This delay is evaluated after the training phase, which helps in directly selecting the best algorithm for the recommendation task. Thereby improving the overall performance of the system-under test.

V. CONCLUSION AND FUTURE WORK

The machine learning algorithm utilizes most of the strong characteristics of already existing algorithms, and learns from their performance in order to generate a trained classifier and recommender system. From the results we can observe that the overall precision is improved by more than 10%, while the recall is improved by more than 12%. This improvement makes the system capable enough for usage in any kind of real-time scenario. Moreover, the improvement in accuracy is more than 8%, which indicates that the system gives an exact recommendation at the output. These advantages make the system usable and applicable for any kind of real-life recommendation environment. Reducing the latency of the learning phase can be a challenge, and must be taken up, so that the overall computational complexity of the system is reduced without reducing the performance. For this purpose, algorithms like advanced Q-learning can be applied, and its performance can be evaluated.

VI. REFERENCES

[1] Rahul, H. Dahiya and D. Singh, "A Review of Trends and Techniques in Recommender Systems," *2019 4th International Conference on Internet of Things: Smart Innovation and Usages (IoT-SIU)*, Ghaziabad, India, 2019, pp. 1-8. doi: 10.1109/IoT-SIU.2019.8777645

[2] X. Zhao, "A Study on E-commerce Recommender System Based on Big Data," *2019 IEEE 4th International Conference on Cloud Computing and Big Data Analysis (ICCCBDA)*, Chengdu, China, 2019, pp. 222-226. doi: 10.1109/ICCCBDA.2019.8725694

November-December 2019
ISSN: 0193-4120 Page No. 6585 - 6591

[3] Nakhli, Ramin & Moradi, Hadi & Sadeghi, Mohammad. (2019). Movie Recommender System Based on Percentage of View. 656-660. 10.1109/KBEI.2019.8734976.

[4] B. Alhijawi, N. Obeid, A. Awajan and S. Tedmori, "Improving collaborative filtering recommender systems using semantic information," *2018 9th International Conference on Information and Communication Systems (ICICS)*, Irbid, 2018, pp. 127-132.

[5] C. M. Wu, D. Garg and U. Bhandary, "Movie Recommendation System Using Collaborative Filtering," *2018 IEEE 9th International Conference on Software Engineering and Service Science (ICSESS)*, Beijing, China, 2018, pp. 11-15. doi: 10.1109/ICSESS.2018.8663822

[6] A. Nawrocka, A. Kot and M. Nawrocki, "Application of machine learning in recommendation systems," *2018 19th International Carpathian Control Conference (ICCC)*, Szilvasvarad, 2018, pp. 328-331.
doi: 10.1109/CarpathianCC.2018.8399650

[7] Zarzour, Hafed & Al-Sharif, Ziad & Al-Ayyoub, Mahmoud & Jararweh, Yaser. (2018). A new collaborative filtering recommendation algorithm based on dimensionality reduction and clustering techniques. 102-106. 10.1109/IACS.2018.8355449.

[8] P. Chu and S. Lee, "A novel recommender system for E-commerce," *2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, Shanghai, 2017, pp. 1-5. doi: 10.1109/CISP-BMEI.2017.8302310

[9] Ruchika, A. V. Singh and M. Sharma, "Building an effective recommender system using machine learning based framework," *2017 International Conference on Infocom Technologies and Unmanned Systems (Trends and Future Directions) (ICTUS)*, Dubai, 2017, pp. 215-219. doi: 10.1109/ICTUS.2017.8286008

[10] R. Mu, "A Survey of Recommender Systems Based on Deep Learning," in *IEEE Access*, vol. 6, pp. 69009-69022, 2018. doi: 10.1109/ACCESS.2018.2880197

[11] R. P. Putra, D. Nurjanah and R. Rismala, "Top-N Recommendation for Shared Account on Book Recommender System," *2018 International Conference on Information Technology Systems and Innovation (ICITSI)*, Bandung - Padang, Indonesia, 2018, pp. 60-65. doi: 10.1109/ICITSI.2018.8696033

[12] Zhang, Shuai et al. "Deep Learning Based Recommender System." ACM Computing Surveys 52.1 (2019): 1–38. Crossref. Web.

[13] Lumbantoruan, Rosni & Zhou, Xiangmin & Ren, Yongli & Bao, Zhifeng. (2018). D-CARS: A Declarative Context-Aware Recommender System (ICDM 2018). 10.1109/ICDM.2018.00151.

[14] M. Fu, H. Qu, Z. Yi, L. Lu and Y. Liu, "A Novel Deep Learning-Based Collaborative Filtering Model for Recommendation System," in *IEEE Transactions on Cybernetics*, vol. 49, no. 3, pp. 1084-1096, March 2019.
doi: 10.1109/TCYB.2018.2795041

[15] R. L. Rosa, G. M. Schwartz, W. V. Ruggiero and D. Z. Rodríguez, "A Knowledge-Based Recommendation System That Includes Sentiment Analysis and Deep Learning," in *IEEE Transactions on Industrial Informatics*, vol. 15, no. 4, pp. 2124-2135, April 2019.

[16] R. L. Rosa, G. M. Schwartz, W. V. Ruggiero and D. Z. Rodríguez, "A Knowledge-Based Recommendation System That Includes Sentiment Analysis and Deep Learning," in *IEEE Transactions on Industrial Informatics*, vol. 15, no. 4, pp. 2124-2135, April 2019.

[17] X. Su, G. Sperlì, V. Moscato, A. Picariello, C. Esposito and C. Choi, "An Edge Intelligence Empowered Recommender System Enabling Cultural Heritage Applications," in *IEEE Transactions on Industrial Informatics*, vol. 15, no. 7, pp. 4266-4275, July 2019.

[18] Shuai Zhang, Lina Yao, Aixin Sun, and Yi Tay. 2019. Deep Learning Based Recommender System: A Survey and New Perspectives. ACM Comput. Surv. 52, 1, Article 5 (February 2019), 38 pages. DOI:https://doi.org/10.1145/3285029

[19] Wei, Jian, Jianhua He, Kai Chen, Yi Zhou and Zuoyin Tang. "Collaborative filtering and deep learning-based recommendation system for cold start items." *Expert Syst. Appl.* 69 (2017): 29-39.

[20] Mu, Ruihui & Zeng, Xiaoqin & Han, Lixin. (2018). A Survey of Recommender Systems Based on Deep Learning. IEEE Access. PP. 1-1. 10.1109/ACCESS.2018.2880197.