A Review for Recommender System Models and Deep Learning

Fainan Nagy El Sisi
Information Systems Department
Faculty of Computers and Information,
Menofia University El Menoufia, Egypt
finan.nagy@ci.menofia.edu.eg

Hatem M.Abdul-Kader
Information Systems Department
Faculty of Computers and Information,
Menoufia University El Menoufia, Egypt
hatem.abdelkader@ci.menofia.edu

Arabi El Said Keshk
Computer Scince Department
Faculty of Computers and Information,
Menoufia University El Menoufia, Egypt
arabi.keshk@ci.menofia.edu.eg

Asma H. Elsaid
Information System Department
Faculty of Computers and Information,
Menoufia University El Menoufia, Egypt
asmaa.elsayed@ci.menofia.edu.eg

***Abstract*- In the big data and data Science age, the advancement in technology accelerated the need to make a choice from a huge amount of various alternatives and this vast amount of online data is a time consuming and very tedious task. Recommendation systems (RS) are an enormous solution to solve information overload problem. Recommendation systems have caught the attention of researchers and companies recently. It can handle data with a huge amount and help the user to make a decision. In this paper we introduce an overview for the traditional recommendation systems models, the recommendation systems advantages and shortcoming, the recommendation systems challenges, common deep learning traditional technology, how deep learning-based recommendation systems works, deep learning for recommendations and open problems and the novel research trends on this field.**

***Key words*-- recommender system, challenges, deep learning, RS open issues, future research directions.**

I. INTRODUCTION

In modern online services RS plays an increasingly important role [1]. To make a choice from various alternatives in every domain, RS collect the user's activities on the web, which consists of explicit activities such as comments and rating, and implicit activities such as buying and browsing, as inputs to generate Recommendation [2]. The output of the RSs can help the users to finding and selecting user's requirements of items effectively from a huge amount of online information [3][4]. The traditional recommender system methods divided into three types: 1) Content-based model [5]-[7] 2) collaborative filtering (CF) based model [8- 10] and 3) hybrid recommendation model [1], [4], [11], [12]. This paper introduce an overview for the traditional recommendation systems models, the recommendation systems advantages and shortcoming, the recommendation systems challenges, common deep learning traditional technology, how does deep learning-based recommendation systems work, deep learning for recommendations and open problems and the novel research trends on this research field. The rest of this paper organized as follows. Section II introduces an overview for the traditional recommendation systems models. Section III shows the recommendation systems advantages and shortcoming, section IV discusses the recommendation systems challenges, section V displays common deep learning traditional technology, section VI describes how does deep learning-based recommendation systems work, section VII illustrates deep learning for recommendations, and section VIII discusses open problems and the novel research trends on this research field.

II. RELATED WORKSS

From [1] state-of-the-art therefore, they discovered that there are two crucial problems that are needed to be addressed: 1) the representations of users and items and 2) the prediction neural networks engineering. A new deep learning CF model is presented by them. The model consists of two phases: 1) learning low-dimensional embeddings for both users and items and 2) a multi view feedforward neural networks are utilized for generating predicted ratings. [17] adopts a graph clustering algorithm to split the road network of a city into smaller road clusters for evaluation the feature set of a road cluster reflects its properties. Their model predicts the pick-up frequencies in unlabeled clusters, and evaluates the passenger-finding potentials of all the road clusters based on supervised learning. The top-K road clusters with the highest passenger-finding potentials are recommended to the taxi drivers. A novel Deep Learning based Matrix Factorization (DLMF) approach for trust-aware recommendation is proposed in [18] DLMF approach contains two phase of learning. In the first phase the users and items' latent feature vectors premier weight are learned by a deep autoencoder. Then, in the second phase, the users and items' final latent feature vectors are learned, by minimizing the proposed objective function. The objective function not only contains the user's properties, but also the effect of the societal impact in the confidence social network. And, they proposed a trust-aware algorithm for societal discovery.

III. THE TRADITIONAL METHODS OF RECOMMENDATION SYSTEMS

Content-based model utilize attributes that are elicited from the user's profile or items description to make recommendations. CF-based model [8], [9] have drawn more attention because their prediction performance is better than the content-based method, in this model, the previous history of interactions of users or items are taken into consideration, such as the rating given to the item by the user. There are two effective CF-based methods: matrix factorization (MF) [13], [14] and restricted Boltzmann machine (RBM) [15], [16]. The user-item ratings matrix are used to extract the latent vectors of the users and the items, MF learns it and picks up the interaction between the user and the item. The recommendation from item side or user side is made by RBM methods via building freelance models for items or users, respectively. Also, the RBM method can't maintain the item-user interaction and they are not deep enough to pick up complex attributes.

A. Content Based Recommender System (CB)

The recommendation in Content based recommender system can be made by using attributes that are picked up from user's profile or items description to make new recommendations [1], [5]-[6], [19]-[21]. Items are filtered dependent on similar content which the user are tasted [20], [22].

B. Collaborative Filtering (CF)

Collaborative filtering technique doesn't consider user or item content information and utilizes a set of similar preferences of users or user's previous history activities [1], [8], [9], [20]. Collaborative filtering techniques divided into two techniques: 1) memory-based and 2) model-based.

1) Memory-based collaborative filtering, it tries to find the similarity between the existing users and the active user, and predict the active user ratings by using the existing users preferences [20]. The important stage in memory-based collaborative filtering algorithms is the computation of the similarity between users or items. To measure the similarity $w_{u,v}$ between two users u and v, or $w_{i,j}$ between two items i and j, Correlation-based similarity is used, this can be achieved by calculating the Pearson correlation or other correlation-based similarities. Pearson correlation measures how far two variables linearly relate with each other [24], [25], [26]. Equation no (1) illustrate the Pearson correlation between two users u and v according to the user based algorithm.

$$W_{u,v} = \frac{\sum_{i\in I}(r_{u,i} - \bar{r_u})(r_{v,i} - \bar{r_v})}{\sqrt{\sum_{i\in I}(r_{u,i} - \bar{r_u})^2}\sqrt{\sum_{i\in I}(r_{v,i} - \bar{r_v})^2}} \quad (1)$$

Where the $i \in I$ where I is the set of items that are rated by both user u and user v., Recommendation system algorithm based on the item, denotes to the set of users $u \in U$ who rated both items i and j, then the Pearson Correlation will be as shown in equation no (2):

$$W_{i,j} = \frac{\sum_{u\in U}(r_{u,j} - \bar{r_i})(r_{u,j} - \bar{r_j})}{\sqrt{\sum_{u\in U}(r_{u,j} - \bar{r_i})^2}\sqrt{\sum_{u\in U}(r_{u,j} - \bar{r_j})^2}} \quad (2)$$

Where $r_{u,i}$ is the user u rating on item i, r_i is the medium of the i^{th} item rated by those users.

The Similarity of Vector based on Cosine is adjusted in neighbor-based collaborative filtering to identify the most similar items or users [24], [25], [26]. Vector cosine similarity between items i and j is given by equation no (3)

$$W_{i,j} = \cos(\underset{i,\ j}{\rightarrow\rightarrow}) = \frac{\vec{i} \cdot \vec{j}}{\|\vec{i}\| * \|\vec{j}\|} \quad (3)$$

Where "•" refers to the dot product of two vectors.

2) Model-based collaborative filtering, Is a model for machine learning based family, based on the learned model by finding patterns in training data which is represented in complex rating the recommendation is made for the user [23], [24].

C. Hybrid recommender system

Hybrid recommendation system is an approach that combines content based techniques and collaborative filtering techniques to obtain best recommendation performance [11], [27]. The implementation of Hybrid approaches can be made in different ways: either by individually Implement both content-based filtering and collaborative filtering and their recommendations are gathered, or some content-based features are combined into a collaborative methods, or some collaborative features are included into a content based filtering, and combine both of content based and collaborative characteristics by building a general consolidative model [28], [23]. Using hybrid methods can help to solve the cold start and the sparsity problems in recommender systems [20].

IV. THE RECOMMENDER SYSTEMS APPROCH ADVANTAGES AND SHORTCOMING

There are many advantage and shortcoming for recommendation system approaches table 1. shows the comparison between them and table 2. shows the comparison between two types of collaborative filtering.

TABLE 1 COMPARISON OF RECOMMENDER SYSTEM APPROACH [20]

	Collaborative Filtering	**Content Based filtering**	**Hybrid filtering**
Number of users	Recommendation depends on much users having identical taste	Recommendati on depend on singular user	Combination of content based and collaborative filtering
Shortcoming	- Cold start - Data sparsity - Scalability - Trustworthiness	- The Limitation of content analysis - Over Specialization	- complexity is Increased - implementation expense is Increased
Advantages	Serendipitous recommendation	User transparency and independence	beat data sparisty and cold start issue

V. RECOMMENDER SYSTEMS CHALLENGES

In this section we will summaries the most common challenges of recommendation systems:

A. *Cold start problem*

This problem is caused by insufficient rating data necessary to calculate the similarity. The problem refers to users who absolutely have not rated or have few ratings, or items which have small rates are expressed by a few numbers of users or which did not rated. These phenomena leading to fail to difficulty in find out the nearest neighbor users or items, and therefore, lead to inaccurate recommendations quality via traditional recommendations algorithms [18].

TABLE 2 COMPARISON BETWEEN TWO TYPES OF COLLABORATIVE FILTERING APPROACH [20][23][24]

CF Categories	**Advantage**	**Shortcoming**
Memory-based collaborative filtering	- implementation is easy - easy to add new and incremental data. - do not need to consider the content of the items being recommended - well scalability with large size of data	- based on the ratings of human - the decrease of performance because data sparisty - recommendation for new items and users is impossible
Model-based collaborative filtering	- scalable to the actual dataset - improve prediction performance - avoiding over fittings is easily	- expensive model-building - suffers from the sparsity, - generate inaccurate recommendations for users who don't provide ratings

B. *Trustworthiness Problem*

Traditional RSs can't differentiate user's creditability there are credible ratings and fake ratings for malicious purposes. so, such ratings should be excluded in recommendation making [18]. On the other side the creditability comes from the Evaluations of certain users, for example, the ratings of users which their profiles have rich history data trusted by users with a little past history data. In this case the problem could be solved by sharing of priorities to the users [27].

C. *Scalability problem*

The number of users and items are increasing dramatically, Most available resources are used to determine users preferences similarity, so the system to be able to recommend the users, it needs more resources for processing the huge amount of information. To overcome this problem this requires physical improvement of the systems and combining different types of available techniques. Some computations are calculated offline to increase speed of the online recommendations [27].

D. *Sparsity problem*

In e-commerce world number of users and items increased continuously, users usually rate just a few items of the available items, the lake of user information and CF sparsity of user-item matrix used for CF makes the the determination process of user interest is very difficult. CF has a lot of difficulties to identify similarity between users, Which leads to negatively prediction process and thus lowers the performance of the recommendation. [18], [24], [27].

VI. DEEP LEARNING TRADITIONAL TECHNOLOGY

Deep learning is a branch of machine learning rise from artificial neural networks [30]. A word deep means multiple hidden layers in the structure of the network. Deep learning extract high-level representation features from low-level features of data [31]. Machine Learning interprets data such as texts, sounds and images [32]. Deep learning is splits into two branches supervised learning and unsupervised learning [33]. In this part, we discuss a fragment of usually used deep learning approaches. Firstly, we introduce the restricted Boltzmann machine (RBM), Deep Belief Network, Deep Reinforcement Learning (DRL), Convolutional Neural Network (CNN), autoencoder (AE), and Recurrent Neural Network (RNN).

A. Autoencoder

Autoencoder (AE) is an unsupervised model; it is a neural network that trying to rebuild its input data into a version of itself in the output layer through the middle hidden layer, bottleneck layer is utilized as an attribute exemplification of the input data. Autoencoder learns the latent feature of the data through rebuilding the input data by coding and decoding process [4], the purpose of network learning is to make the output signal and input signal as similar as possible [4].

There are variations of autoencoders such as contractive autoencoder, sparse autoencoder, variational autoencoder (VAE), denoising autoencoder, and marginalized denoising autoencoder [34], [35]. There are double tracks of using autoencoder to recommender system: 1) using autoencoder to learn lower-dimensional attribute exemplification at the middle layer; or 2) completing the missing of the interaction matrix in the rebuilding layer.

Autoencoder contains three layers in which the number of neurons in the output layer is equal in number to the number of neurons in the input layer, and the number of neurons in the output layer and the input layer are greater than that of in the middle layer. Fig. 1 shows the structure of Autoencoder [4].

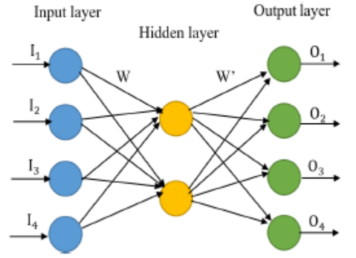

Fig. 1 the structure of Autoencoder [4]

B. Restricted Boltzmann Machine

A two layer neural network is named Restricted Boltzmann Machine (RBM), it made up a hidden layer and a visible layer, there are no intra-layer communications in visible layer or hidden layer, so this the meaning of the word "Restricted" here [34]. It can be easily stacked to a deep net... Boltzmann machine is shown in Fig. 2 [4].

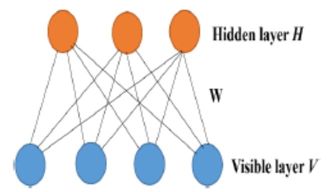

Fig. 2 Restricted Boltzmann Machine [4]

C. Deep Belief Network (DBN)

It is a generative graphical model. The structure of DBN is autoencoders or Restricted Boltzman Machine (RBM) which consists of multiple layers of latent variables. The process of training data in deep belief network is performed layer by layer [36]. To deduce the sub network's hidden layer in each layer the data vector is used, and each sub network's hidden layer of the former Restricted Boltzmann Machine is treated as the visible layer for the following layer of the Restricted Boltzmann Machine network [37]. Its structure is shown in Fig. 3.

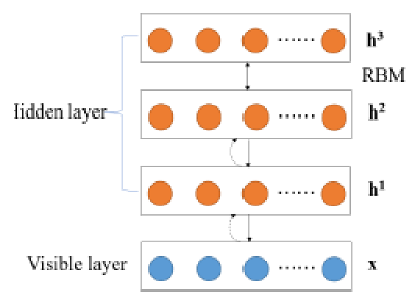

Fig. 3 Restricted Boltzmann Machine [4]

The building of DBN can be considered as stacks of multiple restricted Boltzmann machine. DBN can be composed by incrementing multiple layers and the identical number of nodes. So the training of DBN is simpler than the traditional neural network. DBN model are frequently applied to attribute elicitation and prediction of speech recognition, games, music, images [37], and self-driving cars. etc.

D. Convolutional Neural Network (CNN)

CNN is a particular type of feedforward neural network, with convolution layers and pooling operations. It can pick up the global and local features and significantly improving the accuracy and efficiency. It performs well in processing data with grid-like topology [34].

E. Recurrent Neural Network (RNN)

RNN is fitting for modeling the type of data which called sequential data. At variance feedforward neural network, RNN have loops and stores to store previous computations. Variants like Gated Recurrent Unit (GRU) and Long Short Term Memory (LSTM) network are frequently widespread in practice to finish the vanishing gradient problem [34].

VII. HOW DOES RECOMMENDER SYSTEMS BASED on DEEP LEARNING WORK?

Generally, deep learning (DL) is considered a subfield of ML learning, which consists of multiple layers, which is able to learn multiple levels of representations and abstractions from data. Many of nowadays e-commerce web sites using DL to build better customer background.

Many of recommendation systems based on deep learning have been proposed in last few years. The question is, for which architectures we need to utilize the neural networks, this is determined according to the problem scope and recommendation scenarios. The important advantage that recommendation systems based on deep learning about traditional recommendation systems is dealing with complex interactivity style and accurately extracting the user's tastes. Collaborative filtering Model and Content-based Model are linear systems that can't deal with like complex user patterns.

VIII. RECOMMENDATIONS BASED DEEP LEARNING

To illustrate how each kind of Recommender System works, and the usefulness of it, we show a survey of the most common techniques.

A. Recommendation Systems Based On Convolutional Neural Networks

They are most suitable for processing unstructured multimedia data, and give better attribute elicitation. They have the ability to process the data like image, text, audio, and video.

CNN can Strengthens the traditional systems like collaborative filtering and eliminate cold start problem. This advantage is important for e-business, because the vast majority of customers make their decisions by assessing goods' visuals [38].

CNN is also a choice for non-Euclidean data (non-ordinal or hierarchical data) like social networks, knowledge graph, and protein-interaction networks. For instance, this kind of system could be applied to Pinterest recommendations.

B. *Recommendation Systems Based On Recurrent neural networks*

They become an important advantage for processing data which described as sequential, identify the patterns of sequential user behavior and temporal dynamics of interactions. For instance, YouTube predicts the viewed content for an exact period of the day or estimates the next content according to the actual viewed content.

The most of today internet sites don't interest in the user consumption habits or user access to long-term, because this problem can be solved by session based recommendations (a cookie mechanism).

Session-based recommendations can be constructed by Recurrent Neural Network, even if it does not have user data and can predict what the user will pick up next based on user navigation [38].

C. *Recommendation Systems Based On Restricted Boltzmann Machine*

Restricted Boltzmann Machine and collaborative filtering are integrated for enhance the recommendation process on the streaming web environment. Techniques based on Restricted Boltzmann Machine resulting recommendations with high accuracy because it is scalable to large data size [38].

D. Recommendation Systems Based On Autoencoder

Autoencoder is trying to rebuild its input data into a version of itself in the output layer through the bottleneck hidden layer, the middle hidden layer describes a code used to represent the input. It Containing two process encoder and decoder. The encoder converts the information into the code and the decoder converts the code to rebuild the input. The power of autoencoder is the ability of reducing the dimension of data, reconstruct the data, and attribute elicitation [38].

IX. OPEN ISSUES AND FUTURE DIRECTIONS OF RSS

From the previous related work we conclude some issues that are stilling open problems [1], 1) generating the features of the items and the users from the ratings matrix for deep neural networks, 2) improve time sensitivity for recommender system, 3) sparsity problem is a collaborative filtering recommender systems domain problem. This problem requires from the researchers in this area to find new ways to predict this missing data [39].

- The design of the most nowadays RSs is to pull potential customers. We think that future RSs will become a personal recommender on everything on our daily life [29]. In this section some of the characteristic of future RSs and the practical areas that will strength the RSs are brief.

.

A. Data-driven

In the area of the internet of things (IoT), internet of everything (IoE) and big data, data will be collected from anywhere and for anything, and analysed using these resources of data, RSs will be more intelligent [29].

B. No cold start problem

In future RSs by collecting implicit and suitable information from all connectivity ways, such as Social networks, IoE, and other online sources 'cold start problem' will be expire [29].

C. More customer-centric

Recently RSs are concentrate on seller preferences, Future RSs should be more concentrated to buyers [29].

D. More personalised recommendation

By analysing individual behaviors and habits recommendations will be more individual. Future RSs will be smarter and secure [29].

E. Personalised healthcare recommendation

With the presence of IoT make the research area of Personalised healthcare recommendation plays a important role in providing best and individual healthcare. Such as health supplements, Suitable medicines, demand changes of lifestyle [27], and suitable acknowledgement such as send appropriate messages to depressed patients, and send warning messages to the persons responsible for them in the event that expressions suggestive of suicide or self-harm are discovered [40].

X. CONCLUSIONS

In the era of big data the need to make a choice from a large amount of online information, is a very tedious task. Recommendation systems are an enormous solution to solve information overload problem. In this paper we have introduced an overview for the traditional recommendation systems models, the recommendation systems advantages and shortcoming, the recommendation systems challenges, common deep learning traditional technology, how deep learning-based recommendation systems works, deep learning for recommendations and open problems and the novel research trends on this research field.

REFERENCES

[1] M. Fu, H. Qu, Z. Yi, L. Lu, and Y. Liu, *A Novel Deep Learning-Based Collaborative Filtering Model for Recommendation System,* IEEE, Vol: 49, Issue: 3, 2019.

[2] J. Liu and C. Wu, *Deep Learning Based Recommendation: A Survey ,* Lecture Notes in Electrical Engineering conference, 2017.

[3] X. Su and T. M. Khoshgoftaar, *A survey of collaborative filtering techniques,* USA: Advanced Artificial Intelligent., vol. 12, no. 4, pp. 4_9, 2009.

[4] R. Mu, *A Survey of Recommender Systems Based on Deep Learning,* vol. 12, IEEE access, 2018.

[5] G. Linden, B. Smith, and J. York, *Amazon.com recommendations: Item-to-item collaborative filtering,* IEEE Internet Comput., vol. 7, no. 1, pp. 76–80, Jan./Feb. 2003.

[6] J. Liu, P. Dolan, and E. Pedersen, *Personalized news recommendation based on click behavior*, Hong Kong: in Proc ACM 15th Int, pp. 31–40, Conf. Intell Interfaces, 2010.

[7] R. J. Mooney and L. Roy, *Content-based book recommending using learning for text categorization,* 5th ACM Conf. Digit. Libraries, pp. 195_204, USA: San Antonio, TX, 2000.

[8] R. M. Bell and Y. Koren, *Improved neighborhood-based collaborative filtering,* in Proc. KDD Cup Workshop 13th ACM SIGKDD Int. Conf. Knowl. Disc. Data Min., pp. 7–14, 2007.

[9] B. Li, X. Zhu, R. Li, and C. Zhang, *Rating knowledge sharing in crossdomain collaborative filtering,* IEEE Trans. Cybern., vol. 45, no. 5, pp. 1068–1082, May 2015.

[10] J. S. Breese, D. Heckerman, and C. Kadie, *Empirical analysis of predictive algorithms for collaborative filtering*, Madison, WI, USA: ACM, 14th conference on Uncertainty in artificial intelligence, July 1998,.

[11] G. Adomavicius, A. Tuzhilin,: *Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions,* IEEE Transactions On Knowledge And Data Engineering, vol. 17, no. 6, June 2005.

[12] M. Balabanovi¢ and Y. Shoham, *Fab: Content-based, collaborative recommendation,* Communication of the ACM, vol. 40, no. 3, pp. 66_72,March 1997.

[13] J. D. Rennie and N. Srebro, *Fast maximum margin matrix factorization for collaborative prediction,* Bonn, Germany: *22nd Int. Conf. Mach. Learn.*, pp. 713–719, 2005.

[14] X. Luo et al., *A nonnegative latent factor model for large-scale sparse matrices in recommender systems via alternating direction method*, IEEE Transaction Neural Network and Learning Systems, vol. 27, no. 3, pp. 579–592, Mar. 2016.

[15] R. Salakhutdinov, A. Mnih, and G. Hinton, *Restricted Boltzmann machines for collaborative filtering*, ACM 24th International Conference on Machine Learning, pp. 791–798, June 2007.

[16] Y. Zheng, B. Tang, W. Ding, and H. Zhou, "*A neural autoregressive approach to collaborative filtering,* New York, NY, USA: 33rd International Conference on International Conference on Machine Learning, pp. 764–773, 2016.

[17] R. Wang, Y. Lyu , S. Kwong, Yanhua Li, *TaxiRec: Recommending Road Clusters to Taxi Drivers Using Ranking-Based Extreme Learning Machines,* IEEE Transactions on Knowledge and Data Engineering, vol. 30, no. 3, March 2018

[18] S. Deng, L. Huang, G. Xu, X. Wu, and Z. Wu, *On Deep Learning for Trust-Aware Recommendations in Social Networks,* IEEE *Transactions On Neural Networks And Learning Systems,* vol 28, no. 5, May 2017.

[19] E. Bigdeli; Z. Bahmani, *Comparing accuracy of cosine-based similarity and correlation-based similarity algorithms in tourism recommender systems*, 4th IEEE International Conference on Management of Innovation and Technology, 2008

[20] Basiliyos Tilahun Betru, Charles Awono Onana, Bernabe Batchakui, *Deep Learning Methods on Recommender System: A Survey of State-of-the-art,* Computer Science International Journal of Computer Applications, 2017.

[21] N. Pereira, S. Varma, *Survey on Content Based Recommendation System,* International Journal of Computer Science and Information Technologies Vol. 7, no. 1, 2016.

[22] K. Lang, *Newsweeder learning to filter netnews,* Proceedings of the 12th International Conference on Machine Learning, 1995.

[23] Poonam B. Thorat, R. M. Goudar, Sunita Barve, *Survey on Collaborative Filtering, Content-based Filtering and Hybrid Recommendation System,* International Journal of Computer Applications, 2015.

[24] L. zheng, *A survey and critique of deep learning on recommender systems*, Department of computer science 2016.

[25] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom, and J. Riedl, *An open architecture for collaborative filtering of netnews,* Proceedings of ACM on Computer Supported Cooperative Work, 1994.

[26] X. Su and T. M. Khoshgoftaar, *A Survey of Collaborative Filtering Techniques*, Florida Atlantic University: Advances in Artificial Intelligence, 2009.

[27] F. Mansur, V. Patel, M. Patel, *A Review on Recommender Systems,* 4th International Conference on Innovations in information Embedded and Communication Systems (ICIIECS), 2017.

[28] P. K. Singh, P. K. D. Pramanik A. K. Dey, P. Choudhury, *Recommender Systems: An Overview, Research Trends, and Future Directions,* International, Journal of Business and Systems Research, vol. 15, no. 1, pp. 14–52, 2021.

[29] F.O. Isinkayea, Y.O. Folajimib, B.A. Ojokohc, *Recommendation systems: Principles, methods and evaluation,* Egyptian Informatics Journal, vol. 16, no. 3, pp. 261-273, 2015.

[30] D. Silver et al., *Mastering the game of Go with deep neural networks and tree search,* Nature, vol. 5 , no. 7587, pp. 484_489, 2016.

[31] Y. Shan, R. T. Hoens, H. Wang, D. Yu, J. C. Mao, and J. Jiao, *Deep Crossing: Web-scale modeling without manually crafted combinatorial features,* in Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, San Francisco, CA, USA: 2016, pp. 255_262.

[32] H. Guo, R. Tang, Z. Li, X. He, and Y. Ye, *DeepFM: A factorization-machine based neural network for CTR prediction*, in Proc. 26th International Joint Conference on Artificial Intelligence, pp. 1725_1731, Melbourne, VIC, Australia: 2017.

[33] G. Zhou et al, *Deep interest network for click-through rate prediction*. [Online]. Available: https://arxiv.org/abs/1706.06978, July. 2021.

[34] S. Zhang, L. Yao, A. Sun, and Y, Tay, *Deep Learning based Recommender System: A Survey and New Perspectives,* ACM Computing Surveys, Vol. 1, No. 1, Article 1, 35 pages. 2018.

[35] A. M. Elkahky, Y. Song, and X. He, *A multi-view deep learning approach for cross domain user modeling in recommendation systems,* in Proceedings of the 24th International Conference on World Wide Web, Florence, Italy: pp. 278_288, 2015.

[36] Y. Bengio, *Learning deep architectures for AI,* Foundations and Trends in Machine Learning, vol. 2, no. 1, pp. 1_127, 2009.

[37] X. Wang and Y. Wang, *Improving content-based and hybrid music recommendation using deep learning,* in Proceedings of the 22nd ACM international conference on Multimedia, pp. 627_636, Orlando, FL, USA: 2014.

[38]https://medium.com/sciforce/deep-learning-based-recommender-systems-b61a5ddd5456 August. 2021.

[39] N. Mishra, S. Chaturvedi , A. Vij, and S. Tripathi, *Research Problems in Recommender systems,* Journal of Physics: Conference Series, 2021.

[40] R. L. Rosa, G. M. Schwartz, W. V. Ruggiero, and D. Z. Rodr´ı guez, *A Knowledge-Based Recommendation System that includes Sentiment Analysis and Deep Learning,* IEEE Transactions on Industrial Informatics, vol. 15, no. 4, no. 2124 – 2135, 2019.