Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 5, May : 2024

DCCR DEEP COLLABORATIVE CONJUNCTIVE RECOMMENDER FOR RATING PREDICTION

Dr.K.Rekha Devi Assisstant Professor CSE, *Vaagdevi College of Engineering(Autonomous),India*
Gattikoppula Manisha UG Student,CSE,Vaagdevi College of Engineering(Autonomous),India
Gujjunuri kalyan UG Student,CSE,Vaagdevi College of Engineering(Autonomous),India
Kunduru Naveen UG Student,CSE,Vaagdevi College of Engineering(Autonomous),India
Myakamalla manasa UG Student,CSE,Vaagdevi College of Engineering(Autonomous),India

ABSTRACT
Recently, collaborative filtering combined with various kinds of deep learning models is appealing to recommender systems, which have shown a strong positive effect in an accuracy improvement. However, many studies related to deep learning model rely heavily on abundant information to improve prediction accuracy, which has stringent data requirements in addition to raw rating data. Furthermore, most of them ignore the interaction effect between users and items when building the recommendation model. To address these issues, we propose DCCR, a deep collaborative conjunctive recommender, for rating prediction tasks that are solely based on the raw ratings. A DCCR is a hybrid architecture that consists of two different kinds of neural network models (i.e., an auto encoder and a multilayered perceptron). The main function of the auto encoder is to extract the latent features from the perspectives of users and items in parallel, while the multilayered perceptron is used to represent the interaction between users and items based on fusing the user and item latent features. To further improve the performance of DCCR, an advanced activation function is proposed, which can be specified with input vectors. The extensive experiments conducted with two well-known real-world datasets and performances of the DCCR with varying settings are analyzed. The results demonstrate that our DCCR model outperforms other state-of-art methods. We also discuss the performance of the DCCR with additional layers to show the extensibility of our model.

1. INTRODUCTION
Recommender systems [1] are essential for the success of many online applications. Considering online shopping web- sites as an example, numerous goods are provided by these shopping sites, and users browse all the information about all the goods in a short time. In this context, recommender systems, as one kind of effective information filtering tool, not only can help users to obtain more valuable advice by filtering the redundant information but also gradually increase the sales volume of the websites. As a result, recommender systems have already been integrated in some large-scale web sites (e.g., Amazon), which continually service thousands of people. To date, different kinds of recommendation tasks have been extensively investigated in academia and industry, including rating prediction tasks [11], [13], [25], Top-N tasks [30], [32], [35], click-through rate prediction [12], [27], [29], etc. These tasks can help people to obtain useful information from a certain amount of varied data, which conform to the actual use scenario in industrial applications. In the past few decades, teams of researchers have spent a considerable amount of effort on recommender design and have achieved great results. Collaborative filtering (CF) [1] is one of the great inventions in recommendation research that has been successfully used for industry applications. In contrast to traditional CF recommenders that depend on calculating the similarity between users/items with similar preferences, matrix factorization (MF) is a popular CF recommender for rating prediction tasks [11]. MF decomposes the original rating matrix R into two low-rank matrices, which represent the latent feature space of users and items.
Due to their effectiveness, variants of the MF method have been proposed [2], [9]. Recently, with the success of deep neural networks, the combination with deep learning methods is a new breakthrough for recommenders. In this context, the CF recommender combined with deep learning methods has attracted much attention of academia and industry. Deep learning methods have been successful

applied and have achieved satisfactory results in many fields, such as image processes, speech recognition and natural language processes [3], [18]. Research results have demon- strated that neural networks have the powerful ability to learn the latent features from heterogeneous data and to gain reasonable results [4], [20]. Among them, AutoEncoders (AE) and Multi-Layer Perceptron (MLP) have been widely used for recommendation recently. However, they have their own advantages and disadvantages when designing recommendation model. For AE, it is a common and effective method to reconstruct its input data in the output layer. The core idea of AE for recommender is to predict users' preference via compressing an input vector, and then make recommendations. However, most of existing studies using AE mainly focus on the feature representation with users and items separately, without considering the interaction between them [11], [25], [26]. For MLP, it is a feed-forward neural network with multiple hidden layers, which goods at learning the hierarchical feature representations effectively (e.g., the interaction between users and items in recommendation) but lacks of extracting the feature from user and item separately [9], [32]. It means the feature representation of user and item can be affected by each other. Therefore, it cannot achieve the goals of latent features representation and fusion simultaneously via adopting AE or MLP alone.

To address these issues, this paper proposes a deep col- laborative conjunctive recommender (DCCR). We focus on the rating prediction task of a recommender and format it as a regression problem. By taking advantage of deep learning and traditional CF methods, we try to extract latent features from users' explicit ratings to items without any additional information. We first present some related studies of deep learning methods and traditional methods and analyze the process of rating prediction. We then describe the feature representation with users and items and explain the model that we propose. Some techniques that we apply and the working mechanism are detailed for better features extraction with consideration of the interaction between the users and items.

Particular experimental settings and processes are defined to obtain reasonable results. We test the results with the root mean squared error and the mean absolute error. To obtain the optimal results, some experiments are conducted with varying parameters settings. The experimental results are illustrated to understand the impacts of many factors. We also compare the accuracy of our proposed method with other related and recent methods.

2. PROBLEM STATEMENT

Collaborative filtering (CF) has been widely used to provide users with new products and services in many industrial applications. CF provides users with products from similar users or chooses similar products from users' favorite products. The matrix factorization model is the most important method of CF and has been explored by many researchers. Among different kinds of MF models, the latent factor model (LFM) is the most popular model for rating prediction tasks. The LFM factorizes the rating matrix R into two low-latent factor matrices. However, the manual process of feature extraction consumes manpower and financial resources. Recently, deep learning methods have shown that the neural networks have the powerful ability to automatically learn the features from heterogeneous data and gain reasonable results for most tasks [4], [20]. Therefore, to achieve the goal of improving the prediction accuracy by learning the deep inner user/item features, CF combined with the neural networks methods have been proposed by many papers. As one of the most effective deep learning methods in recommendation, auto encoders have been discussed in several papers [12]_[15]. Auto encoder is an unsupervised learning method that can automatically compress the input features to a low dimension, which has shown absolute advantages in feature extraction compared with traditional methods [22]. Different kinds of auto encoders have been proposed for different scenarios, such as denoising auto encoders (DAE) [4], [5], marginalized auto encoders [6], [12] and contractive auto encoders [26]. Many researchers have successfully applied these models in recommender systems. Reference [12] combines collaborative filtering with marginalized denoising auto encoders for rating prediction and click prediction. Reference [25] employs stacked denoising auto encoders (SDAE) to extract features from side information to predict ratings. Some studies combined with traditional

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 5, May : 2024
method are proposed. In [26], the authors present two new hybrid models by integrating contractive auto encoders (CAE) into the matrix factorization model: SVD, SVDCC [11], which are named AutoSVD and AutoSVDCC. The authors utilize CAE to represent item side information with nonlinear features. In [30], the authors build a hybrid collaborative filtering model that combines the SDAE and MF to learn both a user item rating matrix and side information of users and items. Although an auto encoder is an effective method for compressing an input vector for predicting users' preference and making recommendations, these studies usually focus on the feature representation with users and items separately without considering the interaction between users and items. To address this issue, multilayered perceptron another neural network model has been applied to many industry recommender systems. Multilayered perceptron combines the features of users and items, which have been extracted from neural networks to achieve better recommendation. But most of these methods are focus on the content processing, such as reviews. Normally, the reviews of users and items are employed as input data and a joint deep model are build to merge the features [23]. Some works apply co-attention mechanisms [24] to learn a distributed representation from user and item reviews. Side information, such as categorical information about users and items, is applied in many papers to improve the accuracy of prediction and has been applied for multiple tasks, especially top-n prediction. Reference [31] combines the linearity of the Factorization Machines (FM), which represents the feature interactions and nonlinearity of networks that extract features from high-order interactions such as categorical variables.

Disadvantages

In the existing work, the system doesn’t focus on the rating prediction task of a recommender and format it as a regression problem. The system is less effective due to lack of deep learning.

3. PROPOSED SYSTEM

The system proposes a deep collaborative conjunctive recommender (DCCR). We focus on the rating prediction task of a recommender and format it as a regression problem. By taking advantage of deep learning and traditional CF methods, we try to extract latent features from users' explicit ratings to items without any additional information. We first present some related studies of deep learning methods and traditional methods and analyze the process of rating prediction. We then describe the feature representation with users and items and explain the model that we propose. Some techniques that we apply and the working mechanism are detailed for better features extraction with consideration of the interaction between the users and items. Particular experimental settings and processes are defined to obtain reasonable results. We test the results with the root mean squared error and the mean absolute error. To obtain the optimal results, some experiments are conducted with varying parameters settings. The experimental results are illustrated to understand the impacts of many factors. We also compare the accuracy of our proposed method with other related and recent methods. The main contributions of this paper include: The system presents a novel recommender model that extracts deep inner features of both users and items that solely depend on the explicit ratings and extract the inter- action features. We describe the details of the structure, input vector, loss function and training techniques, which are indispensable for the experiments. The system investigates the impacts of the parameters of the proposed model and analyzes the relations of these parameters on the prediction accuracy. We also pro- vide possible measures for improving the results from different perspectives. An improved activation function for our neural networks is proposed, which can be specified with input vectors. By conducting considerable experiments on two datasets, the results show that the proposed model can achieve better accuracy for this particular rating prediction task. We also discuss the expandability of our model by analyzing the depth of neural networks. Several methods are proposed to adjust the gradient problem of the deep neural networks.

Advantages

The system uses in which CF recommender combined with deep learning methods has attracted much attention of academia and industry. An effective auto recommendation based on user ranking.

4. IMPLEMENTATION

4.1 Admin

In this module, the Admin has to login by using valid user name and password. After login successful he can perform some operations such as Authorizing users, List Users and Authorize,View all Friend request and response,Add Posts,View all Posts with ratings ,View All Recommended Posts,View All Service Usage Reviewed Posts,View all user search History,View Collaborative Filtering based Recommendation,Find Top K Hit Rate in chart

4.2 Friend Request & Response

In this module, the admin can view all the friend requests and responses. Here all the requests and responses will be displayed with their tags such as Id, requested user photo, requested user name, user name request to, status and time & date. If the user accepts the request then the status will be changed to accepted or else the status will remains as waiting.

4.3 Social Network Friends

In this module, the admin can see all the friends who are all belongs to the same site. The details such as, Request From, Requested user's site, Request To Name, Request To user's site.

4.4 All Recommended Posts

In this module, the admin can see all the posts which are shared among the friends in same and other network sites. The details such as post image, title, description, recommend by name and recommend to name.

4.5 Adding Posts

In this module, the admin adds posts details such as title, description and the image of the post. The post details such as title and description will be encrypted and stores into the database.

4.6 User

In this module, there are n numbers of users are present. User should register before performing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user can perform some operations like Register and Login, View your profile,Req for friend, Find Friends, View all your friends, Search Post, My Search History, View Recommends, View User Interests in the pos,View Top K Hit Rate.

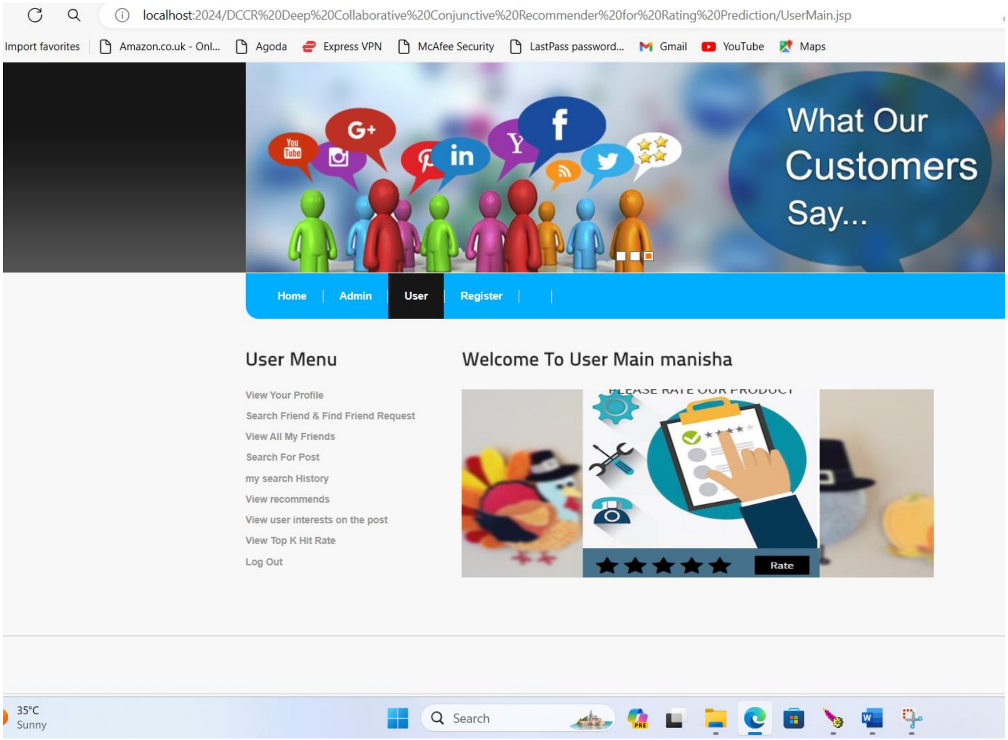
4.7 Searching Users

In this module, the user searches for users in Same Site and in Different Sites and sends friend requests to them. The user can search for users in other sites to make friends only if they have

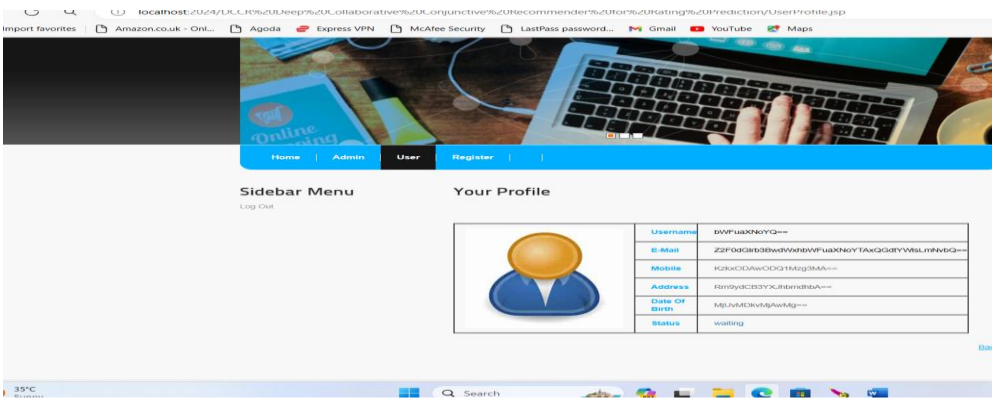
5. RESULT/EXPECTED OUTPUT

Deep Collaborative Conjuctive Recommender For Rating Prediction Home page

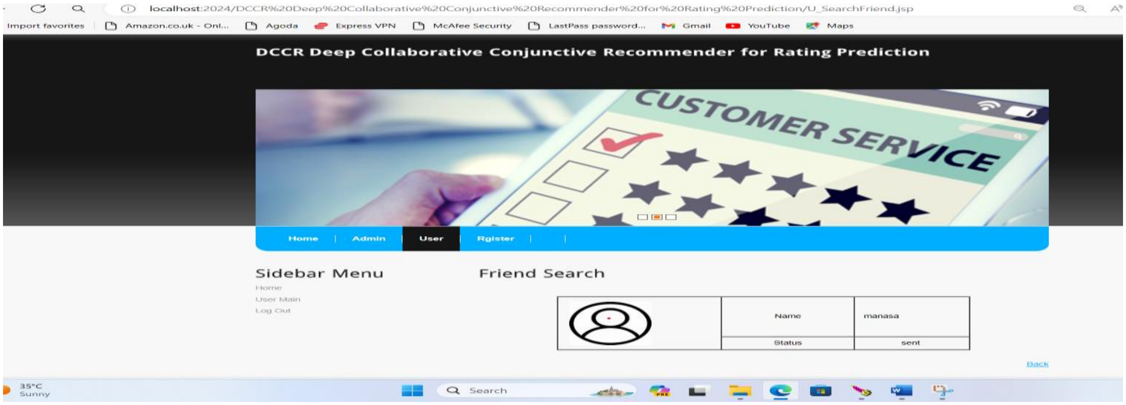
Admin Login Screen with admin details



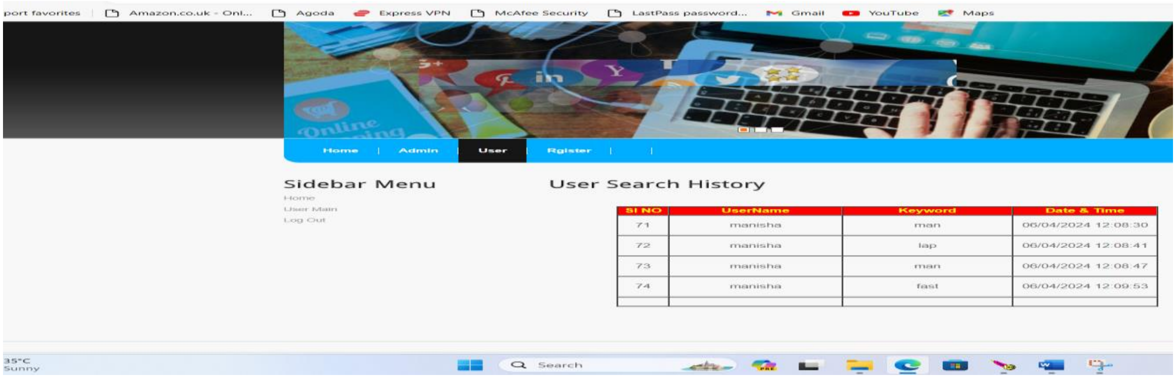
After logging into admin it displays the User Menu with the admin details



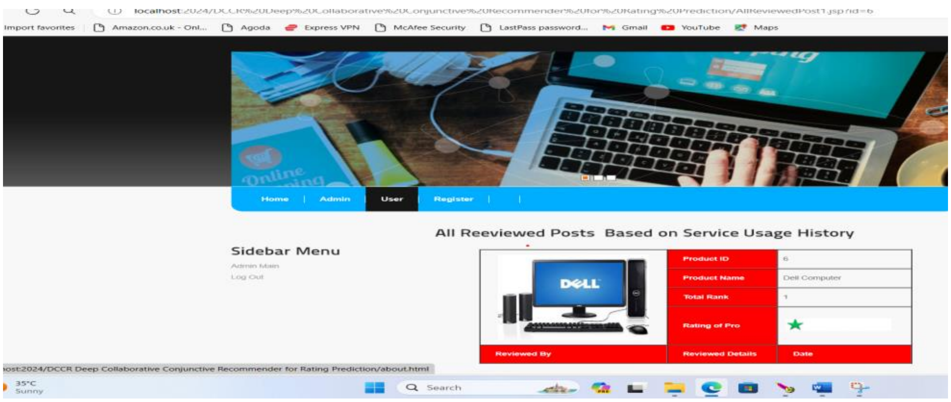
In the User Menu View Your profile



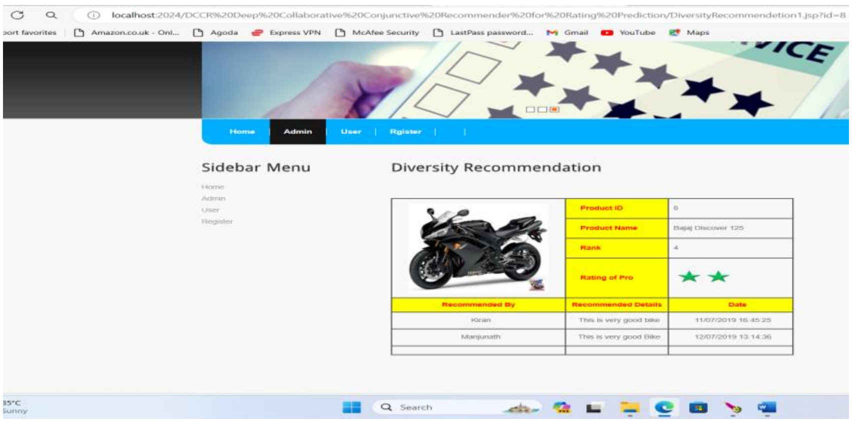
In the user Menu Search for Friend & Find the Friend



The User Search History Was displays here with the user name,keyword and Date & Time

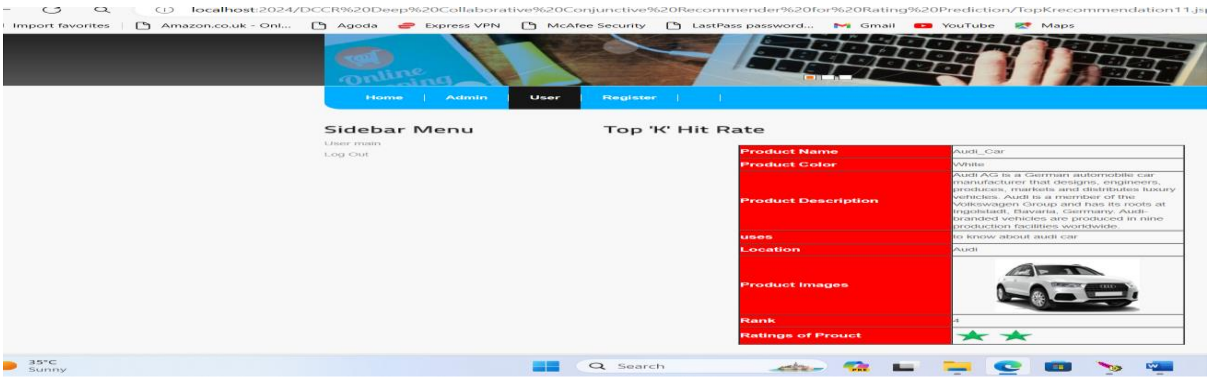


It displays the User Interest on the Product and it views all Reviewed posts



Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 5, May : 2024

View Collaborative Filtering Based Recommendation then it displays the Collaborative Conjuctive and Recommender in Diversity



View the top K Hit Rate Products with the top K Hit Rate value and then it displays the products

5 CONCLUSION

Collaborative filtering has shown to be effective in commercial recommender systems. By combining with neural net- works, CF can represent the latent features of users and item without a manual setting. However, most of related studies use a single model with a common activation function to perform a rating prediction task without considering the traits of features and ratings. In this paper, we propose a hybrid neural network model for rating prediction that is named the deep collaborative conjunctive recommender (DCCR). This model integrates the spirits of several neural networks to separately capture the latent features from users and items and describes the interactions between these features. Solely using the explicit ratings from the data, we design this end- to-end model to improve the accuracy of rating prediction. Numerous factors affect the prediction performance. Thus, to achieve the optimal model, we evaluate the DCCR with varying factor settings by considerable contrast experiments. The results show that our DCCR model outperforms other state-of-the-art methods using two real-world datasets. We also prove that the DCCR with additional layers has a positive effect on accuracy improvement.

6.FUTURESCOPE

A DCCR is a hybrid architecture that consists of two different kinds of neural network models (i.e., an autoencoder and a multilayered perceptron). The main function of the autoencoder is to extract the latent features from the perspectives of users and items in parallel, while the multilayered perceptron is used to represent the interaction between users and items based on fusing the user and item latent features. To further improve the performance of DCCR, an advanced activation function is proposed, which can be specified with input vectors. The extensive experiments conducted with two well-known real-world datasets and performances of the DCCR with varying settings are analyzed. The results demonstrate that our DCCR model outperforms other state-of-art methods. We also discuss the performance of the DCCR with additional layers to show the extensibility of our model.
Collaborative filtering has shown to be effective in commercial recommender systems. By combining with neural networks, CF can represent the latent features of users and items without a manual setting. However, most of related studies use a single model with a common activation function to perform a rating prediction task without considering the traits of features and ratings. In this paper, we propose a hybrid neural network model for ratinGprediction that is named the deep collaborative conjunctive recommender (DCCR).

6. REFERENCES

[1] M. D. Ekstrand, J. T. Riedl, and J. A. Konstan, ``Collaborative filtering recommender systems,'' *Found. Trends Hum.-Comput. Interact.*, vol. 4, no. 2, pp. 81_173, 2011.

[2] R. Kumar, B. K. Verma, and S. S. Rastogi, ``Social popularity based SVDCC recommender system," *Int. J. Comput. Appl.*, vol. 87, no. 14, pp. 33_37, 2014.
[3] A. Krizhevsky, I. Sutskever, and G. E. Hinton, ``Imagenet classi_cation with deep convolutional neural networks," in *Proc. Adv. Neural Inf. Pro- cess. Syst.*, 2012, pp. 1097_1105.
[4] Y. Jhamb, T. Ebesu, and Y. Fang, ``Attentive contextual denoising autoen- coder for recommendation," in *Proc. ACM SIGIR Int. Conf. Theory Inf. Retr.* New York, NY, USA: ACM, 2018, pp. 27_34.
[5] X. Cai, J. Han, and L. Yang, ``Generative adversarial network based heterogeneous bibliographic network representation for personalized citation recommendation," in *Proc. 32nd AAAI Conf. Artif. Intell.*, 2018, pp. 1_8.
[6] Y. Peng, S.Wang, and B.-L. Lu, ``Marginalized denoising autoencoder via graph regularization for domain adaptation," in *Proc. Int. Conf. Neural Inf. Process.* Berlin, Germany: Springer, 2013, pp. 156_163.
[7] P. Baldi and P. J. Sadowski, ``Understanding dropout," in *Proc. Adv. Neural Inf. Process. Syst.*, 2013, pp. 1_9.
[8] J. Deng, W. Dong, R. Socher, L. Li, K. Li, and L. Fei-Fei, ``Imagenet:A large-scale hierarchical image database," in *Proc. IEEE Conf. Comput.Vis. Pattern Recognit.*, Jun. 2009, pp. 248_255.
[9] H. J. Xue, X. Dai, J. Zhang, S. Huang, and J. Chen, ``Deep matrix factorization models for recommender systems," in *Proc. IJCAI*, 2017, pp. 1_7.
[10] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdi- nov, ``Dropout:Asimpleway to prevent neural networks from over_tting," *J. Mach. Learn. Res.*, vol. 15, no. 1, pp. 1929_1958, 2014.
[11] Y. Koren, R. Bell, and C. Volinsky, ``Matrix factorization techniques for recommender systems," *Computer*, vol. 8, pp. 30_37, Aug. 2009.
[12] S. Li, J. Kawale, and Y. Fu, ``Deep collaborative _ltering via marginalized denoising auto-encoder," in *Proc. 24th ACM Int. Conf. Inf. Knowl. Man- age.*, New York, NY, USA: ACM, 2015, pp. 811_820.
[13] S. Sedhain, A. K. Menon, S. Sanner, and L. Xie, ``AutoRec: Autoencoders meet collaborative _ltering," in *Proc. 24th Int. Conf. World Wide Web*. New York, NY, USA: ACM, 2015, pp. 111_112.
[14] D. Liang, R. G. Krishnan, M. D. Hoffman, and T. Jebara, ``Variational autoencoders for collaborative _ltering," in *Proc. World Wide Web Conf. World Wide Web Int. World Wide Web Conf. Steering Committee*, 2018, pp. 689_698.
[15] F. Strub and J. Mary, ``Collaborative _ltering with stacked denoising autoencoders and sparse inputs," in *Proc. NIPS Workshop Mach. Learn. eCommerce*, 2015, pp. 1_9.
[16] Y. LeCun, Y. Bengio, and G. Hinton, ``Deep learning," *Nature*, vol. 521, no. 7553, pp. 436_444, 2015.
[17] S. Ioffe and C. Szegedy, ``Batch normalization: Accelerating deep network training by reducing internal covariate shift," in *Proc. Int. Conf. Int. Conf. Mach. Learn.*, 2015, pp. 1_11.
[18] K. He, X. Zhang, S. Ren, and J. Sun, ``Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2016, pp. 770_778.
[19] F. M. Harper and J. A. Konstan, ``The movielens datasets: History and context," *ACM Trans. Interact. Intell. Syst.*, vol. 5, no. 4, p. 19, 2016.
[20] K. Christakopoulou, ``Q&R: A two-stage approach toward interactive rec- ommendation," in *Proc. 24th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*. New York, NY, USA: ACM, 2018, pp. 139_148.
[21] M. Abadi *et al.*, ``TensorFlow: A systemfor large-scale machine learning," in *Proc. 12th USENIX Symp. Oper. Syst. Design Implement. (OSDI)*, Savannah, GA, USA, vol. 16, Nov. 2016.
[22] F. Zhuang, D. Luo, N. J. Yuan, X. Xie, and Q. He, ``Representation learning with pair-wise constraints for collaborative ranking," in *Proc. 10th ACM Int. Conf. Web Search Data Mining*. New York, NY, USA: ACM, 2017, pp. 567_575.

[23] L. Zheng, V. Noroozi, and P. S. Yu, ``Joint deep modeling of users and items using reviews for recommendation,'' in *Proc. 10th ACM Int. Conf. Web Search Data Mining*. New York, NY, USA: ACM, 2017, pp. 425_434.
[24] Y. Tay, A. T. Luu, and S. C. Hui, ``Multi-pointer co-attention networks for recommendation,'' in *Proc. 24th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*. NewYork,NY, USA:ACM, 2018, pp. 2309_2318.
[25] F. Strub, R. Gaudel, and J. Mary, ``Hybrid recommender system based on autoencoders,'' in *Proc. 1st Workshop Deep Learn. Recommender Syst.* New York, NY, USA: ACM, 2016, pp. 11_16.