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User Based Collaborative Fltering with Recursive Neural Network Prediction Model

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Abstract: Nowadays, with the enormous volume of online data, more consideration has been given to develop information driven recommender systems (RSs). Those schemes automatically guide consumers to discover services or movie with regard to their own interests from a huge set of possible choices. Most RS are employed to recommend the user based on their ratings and their preferences. Hence the existing RS provides very narrow recommendations and it restrict the user from accessing the different products. In this paper a novel Movie Recommender System with Cosine Similarity based Collaborative filtering and Recursive neural network MRS-CCR is proposed to the users based on the movie ratings. In the proposed RS the cosine similarity is utilized for determining the similarity among the users over the rated movies, which is employed to predict the rating of the unrated movie for each user through collaborative filtering. The Collaborative filtering (CF) is more successful recommendation methods because of its simplicity and accuracy. In the present work, matrix factorization technique is used for collaborative filtering. The obtained outcome of collaborative filter is fed into the Recursive neural network which is based on tanh activation function. The Recursive neural network predicts the recommended movies to the user. The outcome of the Recursive neural network is used for constructing the confusion matrix for evaluation. The experimental outcome of MRS-CCR is related to existing system on error and accuracy metrics. The proposed MRS-CCR has the accuracy of 95.53% better than the existing RS.

Keywords: Movie; Recommender systems; Recursive neural network; Collaborative filtering; cosine similarity.

I. INTRODUCTION

Nowadays automatic and initialled recommendations of e-commerce sites are common, and there exists enough item of related recommendations and fulfil the consumer's interests through providing personalized item recommendations. Model the accurate recommender systems has been attention on research in numerous communities and at the centre of numerous items for the past decade. Recommendation system methods have to be advanced in order to recommend specific item to user based on their similarity [1].

Recommender systems (RSs) are software tools that create a suggestion for products that may be a user interest. They may be seen everywhere: there are RSs for music, movies, tourism, books, research articles, news and common items and they even have become a significant component in websites like Netflix, Amazon, YouTube, Google and others [2]. RSs utilize numerous methods like collaborative filtering (CF), content-based ones, and trust-based recommender systems [3]. CF methods are more commonly utilized; they don't necessity any earlier knowledge about consumers or items, instead, they make recommendations with interactions between them. Even though they are effective and simple, they suffer from lot of difficulties, such as prediction accuracy, cold start and incapability of taking difficult interactions between the user and item [4].

CF has been mostly utilized in earlier papers along with that; gradient descent task in RS has attracted numerous researchers to work in this field. The traditional CF didn't measure similarity between dissimilar products through either consumer details and item details, which bounds ability of schemes. Then, if recommend item based on incomplete data, this might chance to loss numerous beneficial items. Traditional data retrieval will rank the item. However, this ranking might recommend item based on popularity. The gradient difficult is usually solved through carry out a hard constraint over standard gradient; the vanishing gradient difficult is normally addressed through RNN.

RNN is an iterative technique for optimizing an objective function by appropriate smoothness possessions that it handles gradient descent difficult utilizing back propagation process. A RNN is a type of deep neural network generated through applying the similar set of weights recursively over a designed input, to yield a structured prediction over variable dimension input structures, or scalar prediction on it, through go over a given arrangement in topological order. The gradient is calculated utilizing back propagation with time utilized for RNN [5].

Prediction accuracy has infrequently been measured through the ability of method to predict upcoming ratings. Relatively, recommendation accuracy has been resulting from a random split of ratings information. Newly, Recommender system uses a RNN to capture variations in both consumer preferences and item perceptions, and extrapolate upcoming ratings in an autoregressive manner [6]. In this paper, a novel CF based recursive neural network to recommend movies through consumer rating information with similarity measures.

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This employs a bottom-up method to generate RNN structures to analyse the enactment of RNN architectures.

Apply RNN method to make comparisons of dissimilar movie through cosine similarity, which will aid the recommendation system to give rating score.

The important contributions of this research are given below,

Improve the recommendation performance by using collaborative filter based on cosine similarity.

RNN network is used to combine the user information and rating class.

Based on RNN's impeccable training, experimental results show the effectiveness of the rating prediction.

The RNN's prediction rate has been calculated and evaluated by using the confusion matrix.

Rest of the paper is organized in the subsequent way: Section 2 comprises the discussion of works done by the researchers previously; Section 3 explains the methodology proposed; Section 4 presents all the simulation outcomes and their inferences; and Section 5 delivers a conclusion.

II. RELATED WORKS

CF may be separated into two common classes: model-based and neighborhood approaches. A neighborhood-based technique uses user–item ratings directly to create recommendations through computing the similarities among user-based or between item-based [7]. A model-based technique uses these user–item ratings with the intention of learn a predictive method and later used this method to create recommendations. The model-based approaches are like Bayesian Clustering, Latent Semantic Analysis (LSA), Latent Dirichlet Allocation (LDA), and Support Vector Machines (SVM), [8]. This technique maps both items and consumers to a combined latent factor space of similar dimension; latent space signifies the latent features of consumers or items [2].

Hidasi et al. [9] presented the session-based recommendation method, GRU4Rec, based GRU. The input is considered as the original state of session with 1-of-N encoding, where N is the quantity of items and if the coordinate is 1 means, the corresponding item is active in this session, otherwise 0. The outcome is probability of being the following in session for every item. Session-parallel mini-batches algorithm is used for the train process and a sampling method for output.

Wu et al. [10] presented the session-based recommendation method for actual-world e-commerce web. It uses the basic RNNs to predict consumer buy subsequent based on click past. To minimalize the computation costs that keeps a finite amount of latest states while collapsing the old states into a single past state. This technique aids to balance the trade-of among prediction accuracy and computation costs. Quadrana et al. [11] presented the session-based RSs with hierarchical RNN. This method may cope with both session aware recommendations while consumer identifiers are present. The above-mentioned three session-based methods don't deliberate any side info. Two extensions designated that side info has effect on improving the quality of recommendation.

Hidasi et al. [12] presented the session-based recommendation of parallel architecture which uses 3 GRUs to study depictions from identity on one-hot vectors, image feature vectors, text feature vectors and one-hot vectors. Outcome of these three GRUs are weightily concatenated and nourished into a non-linear activation to predict the following items in that session. Smirnova et al. [13] presented the context-aware session-based RS based on conditional RNNs. It injects context info into input and outcome layers. Experimental outcomes of these two methods propose the incorporated supplementary info outperform those solely based on past interactions.

Wu et al. [14] presented the LSTM-based method that implicitly captures numerous recognized temporal designs in movie ratings information without explicit inclusion in the method, to learn dynamic embedding of consumers and movies. The next-basket recommendation method was proposed for variable representation of consumer and captured worldwide sequential features between baskets to reflect the consumer's dynamic intent at dissimilar times and interactions of altogether baskets of consumer over time. Park et al. [15] presented the modified User-based CF technique namely Session-Based CF (SSCF), that usages info from same sessions to capture sequence and repetitiveness in listening procedure. Lately, scholars have successfully adopted deep learning methods in RS. In specific, RNN which is proficient of learning methods from sequentially ordered information in the form of natural choice for sequence modelling [4]

Dong et al. [16] presented the improved RNNs and MF method through combining them in multi-task learning framework, where they performed combined optimization by shared method parameters enforcing into two portions. Liang et al. [17] presented the RNN to extract the item and consumer profiles from consumer defined items' tags and their tagging behaviours. But, these session-based approaches regard consumer preference for items as stationary possessions and hence can't capture the altering contextual interactions among user and items.

III. RESEARCH METHODOLOGY

Neural networks (NNs) by manifold feed-forward or recurrent hidden layers have emerged as state-art-of compressing recursive neural networks (RNNs), especially Collaborative filter (CF) based RNN models. To demonstrate the generalization of conventional inter-layer matrix factorization methods, that compress both recursive and inter-layer weight matrices, permits us to compress the methods by negligible amount of loss in accuracy. Fig 1. Shows the overall design flow of Collaborative filter based on recursive neural networks (RNN) model.

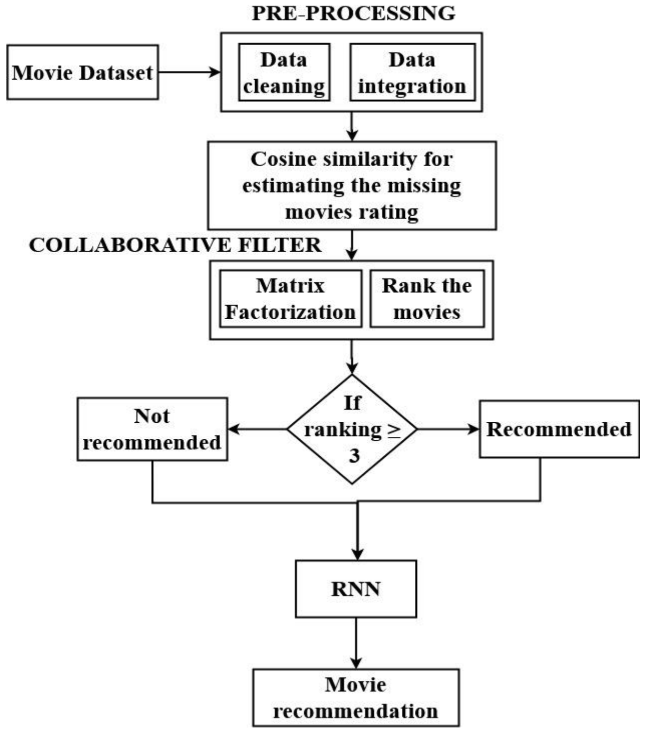

Fig. 1.Overall framework of Collaborative filter based on RNN

Collaborative recommender system

Collaborative filtering is a RS based on consumer's historical behaviour. CF is separated into two categories, they are considering as user based and item (movie) based. Assume there are m users and n movies, we use a matrix through dimensions of m*n to signify the historical behaviour of consumers. Every cell in the matrix denotes the connected opinion that consumer holds. For example, M {i, j} represents how consumer i likes movie j. As such the matrix is named as utility matrix. CF is fulfilling the unfilled cell in utility matrix that consumer does not seen the rated beforehand based on similarity among users or movies. Two kinds of opinions are named as explicit opinion and implicit opinion.

Afterward executing Pre-processing stage, CF is employed as a Matrix Factorization algorithm. Matrix decomposition and fast factorizing algorithm that attempts to carry out same movie Ratings. Then collaborative scheme will recommend top rated movie is elected for every consumer. Afterward that portion, deep learning algorithm is practical on dissimilar movie ratings for every movie. Then, rating predicting for every movie is performed through by its recommender's method on movie wise.

Matrix factorization (MF) is a normal rating prediction method that only uses ratings. MF based approaches have been utilized in broad range of uses like recommending web pages, movies, books, services and relevant research. Fig 2 shows the matrix factorization size of m×n, where m signifies the quantity of user and n signifies the quantity of movies and x signifies the quantity of missing values. In MF based methods, the consumer preference matrix is approximated as a product of lower-rank latent feature matrices demonstrating consumer profiles and movie profiles correspondingly. In the standard matrix factorization, the recommendation undertaking may be formulated as inferring lost values of a partially observed user-item matrix.

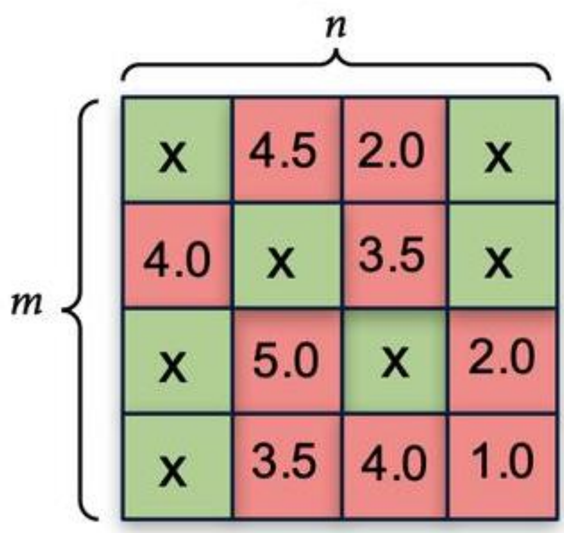

Fig. 2.Matrix factorization

Used based CF that calculate the similarity between consumers. Cosine similarity is utilized to measure the similarity functions. Let u {i, k} represents the similarity among consumer i and consumer k and v {i, j} represents the rating that consumer i gives to movie j by v {i, j}, consider as if the consumer has not rated that movie. This may be expressed as the subsequent manner

$$\cos(u_i - u_j) = \frac{\sum_{k=1}^{m} v_{ik} v_{jk}}{\sqrt{\sum_{k=1}^{m} v_{jk}^2 \sum_{k=1}^{m} v_{ik}^2}} \quad (1)$$

The consumers' opinion on unrated movies may be predicted through utilizing the subsequent equation

$$v_{ij}^{*} = k \sum_{v_{kj} \neq ?} U_{jk} v_{kj} \quad (2)$$

Similarly, the similarity may be calculated for movie-based CF recommends movie with their similarity by the target consumer rated through by Cosine Similarity. CF is utilized to decrease both the dimensionality and data sparsity. Deep learning method is utilized to approximation consumer rating for every movie and likewise very apparent similarity among movies. For this purpose, traditional collaborative algorithm utilized to discover the top most movies based on MF. This is mostly utilized to discover correlated ratings of every movie. CF is fast manner to discover out most associated movies which are at the similar ratings. The maximum associated movie ratings correlated features are additional to dataset. Adding of related movie and its features enables RNN algorithm to learn enhanced within dissimilar hidden layers at similar weight throughout the Network. The outcome of CF method is transmitted into the RNN system that creates its final decision. Predicting solutions must be scalable, process huge quantities of movie data, and extract a best from ratings.

Recursive neural network

Deep learning may be usually deliberated to sub-field of machine learning. A recursive network is just a simplification of recurrent network.

In recurrent net the weights are shared and the dimensionality remains constant together with the length of sequence since it cope with position-dependent weights while run into a sequence order at experiment time of dissimilar length at training time. But in recursive net the weights are shared and dimension size are constant at each node for similar reason. This means that altogether the *Wxh* weights will be shared equally and consequently will be *Whh* weight and since it is a single neuron which has been unfolded in time. General diagram of RNN is shown in fig 3.

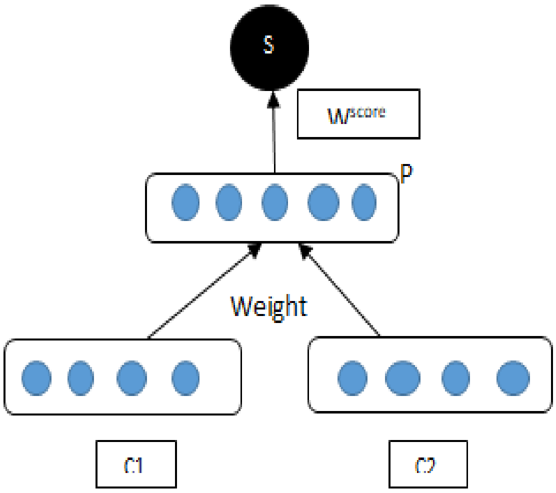

Fig. 3.General diagram of Recursive Neural Network

Nodes are jointed into parental utilizing a weight matrix that is shared across the entire net, and non-linearity like *tanh*. If c_1 and c_2 are *n*-dimensional vector depiction of nodes, their parental will likewise be an *n*-dimensional vector, it can be computed by using below expression

$$P_{1,2} = \tanh(W[C1, C2]) \qquad (3)$$

Where *W* denotes the learned $[n \times 2n]$ weight matrix, *tanh* function of RNN is shown in the below fig 4.

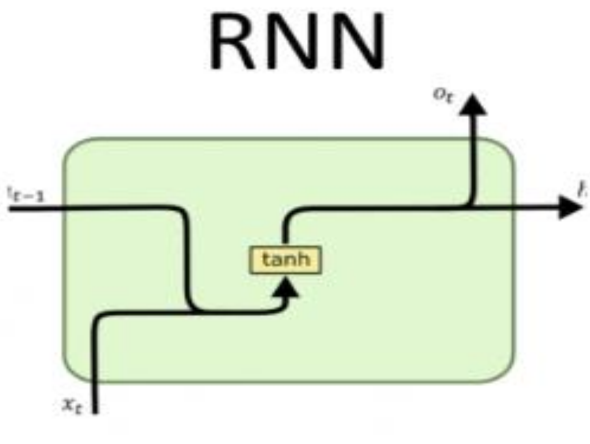

Fig. 4.tanh function in RNN

RNNs is additional like a hierarchical net where there is actually no time aspect to input sequence however the input has to be deal with hierarchically in tree function. It displays the manner to learn a parse tree of sentence through recursively taking the outcome of function performed on lesser chunk of text. A RNN is employed as deep learning algorithm. RNN is trained by back-propagation. Every weight is adjusted consistent with its contribution value to the error. Afterward the accomplishment of training function, where the model parts are trained individually without recognize each other, this method is utilized to predict the consumer overall rating of movies that has not rated yet. The recommendation procedure take place as shown in Fig. 1, the overall movie ratings are obtained as the subsequent way.

Step 1: Initially, the consumer ID and movie ID are get pairs and feed as inputs to the criteria ratings RNN, and the normalize predicted criteria ratings are obtained as $r_1, r_2, \ldots r_k$

Step 2: To compute the overall ratings, the normalize criteria ratings $r_1, r_2, \ldots r_k$ that computed in step 1, was fed as inputs to obtain the overall ratings from RNN, and then it predict the overall ratings 'r'.

Step 3: Finally, recommend the optimal movie to the consumer utilizing the overall rating 'r' as in traditional rating recommender systems.

IV. RESULTS AND DISCUSSION

To evaluate the effectiveness of CF based RNN method in terms of rating prediction through using python tool. Furthermore, like movie ID, consumer ID and other rating, are combined to the method as new variables. Since it is recognized that there is a certain correlation between user ratings at dissimilar movies, this work enriched the dataset by the movie ratings.

Root Mean Squared Error (RMSE)

Root mean squared error (RMSE) is a normal evaluation metric for supervised regression method for prediction ratings. RMSE measures the dissimilarities between predicted ranges by the model and noticed value. The RMSE value can be is computed by using the following expression.

$$RMSE = \sqrt{\frac{\sum(\hat{r}_{ui} - r_{ui})^2}{\#\ of\ ratings}} \qquad (4)$$

The experimental result of proposed CF based RNN model provides the better RMSE of 0.32 as compared with the PMF (Mnith et al., 2008), SVD (Sarwar et al., 2002), MLP (He et al., 2017) and JRL (Zhang et al., 2017). The comparison of RMSE with various methods are shown in the below fig 5.

Mean Absolute Error (MAE)

MAE measures the absolute value of dissimilarity between the forecasted range and the real range, which expresses the error range from the forecast on average. Lesser value of MAE signifies the greater accuracy of recommendation ratings. MAE value can be is computed by using the following expression

$$MAE = \frac{\sum |r_{ui} - \hat{r}_{ui}|}{\#\ of\ ratings} \qquad (5)$$

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The experimental outcome of proposed CF based RNN model provides the better MAE of 0.26 as compared with the PMF (Mnith et al., 2008), SVD (Sarwar et al., 2002), MLP (He et al., 2017) and JRL (Zhang et al., 2017). The comparison of MAE with various methods are shown in the below table 1 and fig 5.

Table 1: Error performance of different Recommender system

S.No.	Recommendation system	RMSE	MAE
1	PMF	0.821	0.652
2	SVD	0.815	0.631
3	MLP	0.814	0.63
4	JRL	0.795	0.61
5	Proposed	0.325	0.265

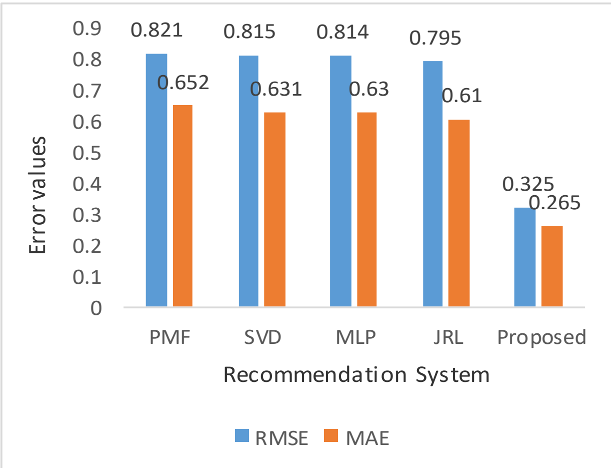

Fig. 5.Comparison of RSME and MAE with various techniques

Confusion matrix

Confusion Matrix is the beneficial machine learning technique that permits to measure the parameters like Precision, Recall, and Accuracy. Below example is given to recognize the terms TP, TN, FN, and TN. Fig 4 displays the confusion matrix table in terms of predicted class and actual class.

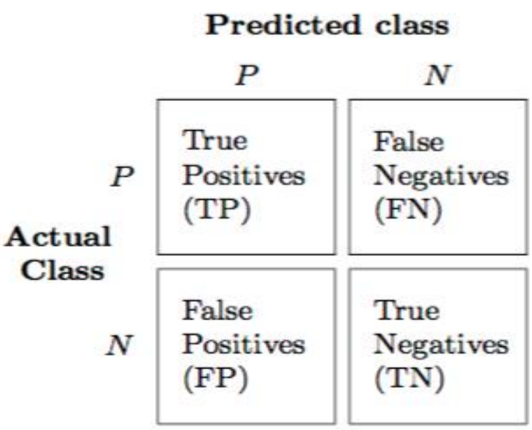

Fig. 6.Confusion Matrix table

- True Positive that predicted the ranges exactly predicted as real positive
- False Positive that predicted the ranges wrongly predicted as real positive it means Negative ranges predicted as positive value.
- False Negative denotes the Positive values are predicted as negative
- True Negative denotes the Predicted values correctly predicted as an actual negative

Accuracy

Accuracy might be calculated by the percentage of properly classified instances as given below

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \qquad (6)$$

Where TP, FP, FN and TN specify the quantity of true positives, false negatives, false positives and true negatives, correspondingly. The experimental result of proposed CF based RNN model provides the better accuracy of 95.53% as compared with the SVM [18], GRU [19], and LSTM [20]. The comparison of accuracy with various methods are shown in the below table 2 and fig 7.

Table 2: Accuracy of different Recommender system

S.No.	Recommendation system	Accuracy
1	SVM	76.20%
2	GRU	83.10%
3	LSTM	82.60%
4	Proposed	95.53%

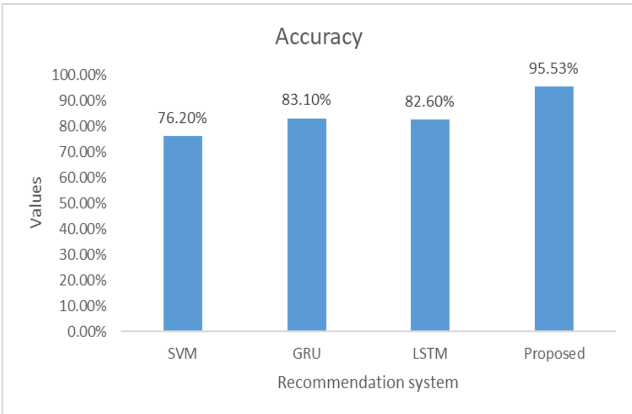

Fig. 7.Comparison of accuracy with various techniques

V. CONCLUSION

Recommender Systems plays a vital role in helping users in identify interested items in online services. General Recommender has been extensively analysed in the past decade and its target to provide the preferences of consumer's past interactions by movies, like ratings. One of the most successful techniques in this setting is collaborative filtering based upon matrix factorization (MF), which learns user and movie ID to design the underlying user preferences.

In this paper a novel cosine similarity based Collaborative filtering with Recursive neural network (RNN) to recommend different movie based on estimated ratings. The cosine similarity is established among eth users to predict the potential rating of unrated movies. Collaborative filtering (CF) is a successful RSs method owing to its effortlessness and attractive accuracy. An end-to-end model with based on recursive neural network to predict the user's recommendation of movie ratings. The experimental result of CF based RNN provides the exact movie ratings and it obtained the RMSE value as 0.32, MAE value as 0.26, and provides the better accuracy as 95.53%. The RNN's prediction rate has been calculated and evaluated by using the confusion matrix.

REFERENCES

1. Lucas, J. P., Luz, N., Moreno, M. N., Anacleto, R., Figueiredo, A. A., & Martins, C. (2013). A hybrid recommendation approach for a tourism system. Expert systems with applications, 40(9), 3532-3550.
2. F. Ricci, Lior, R. Bracha (Eds.), Recommender Systems Handbook, second ed., 2015, http://dx.doi.org/10.1007/978-1-4899-7637-6.
3. C. Porcel, A. Ching-López, G. Lefranc, V. Loia, E. Herrera-Viedma, Sharing notes: An academic social network based on a personalized fuzzy linguistic recommender system, Eng. Appl. Artif. Intell. 75 (2018) 1–10.
4. M. Fu, H. Qu, Z. Yi, L. Lu, Y. Liu, A novel deep learning-based collaborative filtering model for recommendation system, IEEE Trans. Cybern. (2018)
5. Sukhbaatar, S., & Fergus, R. (2016). Learning multiagent communication with backpropagation. In Advances in neural information processing systems (pp. 2244-2252).
6. Ping, W., Peng, K., & Chen, J. (2018). Clarinet: Parallel wave generation in end-to-end text-to-speech. arXiv preprint arXiv:1807.07281.
7. Herlocker, J. L., Konstan, J. A., Borchers, A., & Riedl, J. (2017, August). An algorithmic framework for performing collaborative filtering. In ACM SIGIR Forum (Vol. 51, No. 2, pp. 227-234). New York, NY, USA: ACM.
8. D.M. Blei, A.Y. Ng, M.I. Jordan, Latent dirichlet allocation, J. Mach. Learn. Res. 3 (2003) 993–1022,
9. Balazs Hidasi, Alexandros Karatzoglou, Linas Baltrunas, and Domonkos Tikk. 2015. Session-based recommendations with recurrent ´ neural networks. International Conference on Learning Representations (2015)
10. Sai Wu, Weichao Ren, Chengchao Yu, Gang Chen, Dongxiang Zhang, and Jingbo Zhu. 2016. Personal recommendation using deep recurrent neural networks in NetEase. In ICDE. 1218–1229.
11. Massimo ‹adrana, Alexandros Karatzoglou, Balazs Hidasi, and Paolo Cremonesi. 2017. Personalizing session-based recommendations ´ with hierarchical recurrent neural networks. In Recsys. 130–137.
12. Balazs Hidasi, Massimo ‹adrana, Alexandros Karatzoglou, and Domonkos Tikk. 2016. Parallel recurrent neural network architectures ´ for feature-rich session-based recommendations. In Recsys. 241–248.
13. Elena Smirnova and Flavian Vasile. 2017. Contextual Sequence Modeling for Recommendation with Recurrent Neural Networks. (2017).
14. Wu, C.Y.; Ahmed, A.; Beutel, A.; Smola, A.J.; Jing, H. Recurrent recommender networks. In Proceedings of the 10th ACM International Conference on Web Search and Data Mining, Cambridge, UK, 6–10 February 2017; pp. 495–503
15. Park, S.E.; Lee, S.; Lee, S.G. Session-based collaborative filtering for predicting the next song. In Proceedings of the IEEE 2011 First ACIS/JNU International Conference on Computers, Networks, Systems and Industrial Engineering (CNSI), Jeju Island, Korea, 23–25 May 2011; pp. 353–358
16. Dong, D.; Zheng, X.; Zhang, R.; Wang, Y. Recurrent Collaborative Filtering for Unifying General and Sequential Recommender. In Proceedings of the 27th International Joint Conference on Artificial Intelligence, Stockholm, Sweden, 13–19 July 2018; pp. 3350–3356.
17. Liang, N.; Zheng, H.T.; Chen, J.Y.; Sangaiah, A.K.; Zhao, C.Z. TRSDL: Tag-Aware Recommender System Based on Deep Learning–Intelligent Computing Systems. Appl. Sci. 2018, 8, 799. doi:10.3390/app8050799
18. Huang, Z., Chen, H., Hsu, C. J., Chen, W. H., & Wu, S. (2004). Credit rating analysis with support vector machines and neural networks: a market comparative study. Decision support systems, 37(4), 543-558.
19. Chung, J., Gulcehre, C., Cho, K., & Bengio, Y. (2014). Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555.
20. Gers, F., Schraudolph, N., & Schmidhuber, J. (2002). Learning precise timing with LSTM recurrent networks. Journal of Machine Learning Research, 3, 115–143
21. Micheli, A.; Sona, D.; Sperduti, A. (2004-11-01). "Contextual processing of structured data by recursive cascade correlation". IEEE Transactions on Neural Networks. 15 (6): 1396–1410.
22. Hammer, Barbara; Micheli, Alessio; Sperduti, Alessandro; Strickert, Marc (2004). "Recursive self-organizing network models". Neural Networks. 17 (8–9): 1061–1085.
23. Pascanu, Razvan, Mikolov, Tomas, and Bengio, Yoshua. On the difficulty of training recurrent 307 neural networks. arXiv preprint arXiv:1211.5063, 2012.
24. Ruocco, M.; Skrede, O.S.L.; Langseth, H. Inter-Session Modeling for Session-Based Recommendation. In Proceedings of the 2nd Workshop on Deep Learning for Recommender Systems, Como, Italy, 27–31 August 2017; pp. 24–31
25. Zhang, Y. , Ai, Q. , Chen, X. , & Croft, W. B. (2017b). Joint representation learning for top-n recommendation with heterogeneous information sources. In CIKM (pp. 1449–1458). ACM .
26. He, X. , Liao, L. , Zhang, H. , Nie, L. , Hu, X. , & Chua, T.-S. (2017). Neural collaborative filtering. In WWW (pp. 173–182).
27. Sarwar, B. , Karypis, G. , Konstan, J. , & Riedl, J. (2002). Incremental singular value decomposition algorithms for highly scalable recommender systems. In ICCIS (pp. 27–28). Citeseer .
28. Mnih, A., & Salakhutdinov, R. R. (2008). Probabilistic matrix factorization. In NIPS (pp. 1257–1264).

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