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Distributed Improved Deep Prediction for Recommender System using an Ensemble Learning

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Abstract—If online businesses possess valuable interest for suggesting their items by scoring them, then digital advertising gains their profits depending on their promotions or marketing task. Web users cannot be certain that the products handled via big-data recommendation are either advanced or interesting to their needs. In recent decades, recommender system models have been widely used to analyses large quantities of information. Amongst, a Distributed Improved Prediction with Matrix Factorization (MF) and Random Forest (RF) called DIPMF model exploits individual's desires, choices and social context together for predicting the ratings of a particular item. But, the RF scheme needs high computation power and time for learning process. Also, its outcome was influenced by the training parameters. Hence this article proposes a Distributed Improved Deep Prediction with MF and ensemble learning (DIDPMF) model is proposed to decrease the computational difficulty of RF learning and increasing the efficiency of rating prediction. In this DIDPMF, a forest attribute extractor is ensemble with the Deep Neural Network (fDNN) for extracting the sparse attribute correlations from an extremely large attribute space. So, incorporating RF over DNN has the ability to provide prediction outcomes from all its base trainers instead of a single estimated possibility rate. This fDNN encompasses forest module and DNN module. The forest module is employed as an attribute extractor to extract the sparse representations from the given raw input data with the supervision of learning outcomes. First, independent decision trees are constructed and then ensemble those trees to obtain the forest. After, this forest is fed to the DNN module which acts as a learner to predict the individual's ratings with the aid of novel attribute representations. Finally, the experimental results reveal that the DIDPMF outperforms than the other conventional recommender systems.

Keywords-big-data; recommender systems; DIPMF; forest deep neural network; decision trees; rating prediction

I. INTRODUCTION

Big data has emerged as a prominent method of achieving success in a variety of industries, comprehensive constraints, and federal agencies in these modern decades. Big data are frequently defined as sets of data whose quantity exceeds the capability of conventional technologies for accumulating, processing, and evaluating information in a desirable time complexity. The challenge is to identify and assess massive amounts of data to find relevant data for specific goals [1]. With the significant advancement of information available on the network, individuals may experience the major challenge of incredible suggestions, known as the information overload issue. It is difficult for individuals to access unique relevant information. It also increases the need for efficient data collection and analysis to assist individuals in retrieving relevant items like logs, videos, and texts according to their requirements [2].

To address such issues, recommender system models have been established, that provide individuals with flexible opinions related to past desires and interests [3]. Digital marketing, e-government, e-commerce, e-learning, and other real-time applications are exemplars. Collaborative Filtering (CF) is the most beneficial strategy for sentiment analysis [4]. This strategy is usually subcategorized into model-based and memory-based CFs. Model-based strategies provide opinions depending on the statistical solutions, whereas memory-based strategies, such as client-based and item-based CFs, predict undefined opinions by retrieving the preferences of extremely similar clients or items, respectively [5].

Presently, many real-time big-data principles, as well as the rapid development in the number of individuals, items, and other information, have created significant challenges for classic recommender system models. The requirement to assess the individual's desires and interests has made it crucial for retrieving large quantities of information. Even if most recommender systems have proven to be more efficient with less information, they are difficult to execute in a big-data paradigm. In specific, learning of huge amounts of

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information is extremely costly, limiting its applicability in real scenarios [6].

In addition, defining different possibilities should perform the offline prediction. It measures costs over a wide range for increasing data sizes. As well, information granularity is a great concern because it greatly influences of suggestions. Therefore, formulating high-level recommender system models requires knowledge from a variety of difficulties, such as coping with generalization ability, reducing time complexity, improving rating quality, and assessing large amounts of information. From this perspective, a Distributed Predictive Model for optimized suggestions (DPM), an Improved DPM (DPMI) and Distributed Predictive model with MF and RF (shortly called DPMF) have been designed using information partition and alternative learning phase [7]. These models have been pipelined using the Apache Spark framework to enhance the quality of suggestions. But, the DPMF utilizes only individual desires and choices while other contextual data were essential for improving the prediction efficiency.

As a result, a DIPMF model [8] has been developed which enhances the prediction efficiency by assessing the aspects of social context and their dynamic response of each individual for every product. The key purpose of DIPMF was to merge the information from the individual desires, choices and social context. The social context of individuals includes a variety of context attributes such as deviations in current choice with previous choice, characteristics, association, and connections. In typical, individuals are typically associated together through experiences. Primarily, the training set of data was partitioned into an optimized number of parts to accelerate the parallel and distributed learning. Then, the learning process was conducted by the distributed predictive MF with DIPM-Improved variant (DIPMI) which defines all individuals' desires, choices and social context in the training data. Also, the rating estimation was devised as a regression issue and resolved by the RF scheme which estimates the individual's rating manner according to their opinions and social context for all items. In contrast, the RF scheme needs high computation power and time for learning process. Also, its outcome was influenced by the learning variables.

Therefore in this paper, a DIDPMF model is proposed which lessens the computational difficulty of RF and improves the prediction efficiency. In this DIDPMF, a forest attribute extractor is ensemble with the DNN (fDNN) for extracting the sparse attribute correlations from an extremely large attribute space. So, incorporating RF over DNN has the ability to provide prediction outcomes from all its base trainers instead of a single estimated possibility rate. This fDNN encompasses forest module and DNN module. The forest module is employed as an attribute extractor to extract the sparse representations from the given raw input data with the supervision of learning outcomes. First, independent decision trees are constructed and then ensemble those trees to obtain the forest. After, this forest is fed to the DNN module which acts as a learner to predict the individual's ratings with the aid of novel attribute representations. Thus, this DIDPMF can enhance the quality of predicting the item ratings with the reduced time complexity.

The remaining sections of this paper are arranged as follows: Section II discusses the works related to the big-data recommendation systems. Section III describes the methodology of DIDPMF and Section IV displays its testing efficiency. Section V concludes the entire article and advises future improvement.

II. Literature Survey

A new 2-phase deep learning-based suggestion framework [9] has been developed which exploits the low-cost deep learner for initiating another high-efficiency deep learner. In this primary phase, 2 independent marginalized stacked denoising auto-encoders were employed to the clients and product attributes for training the latent component vectors. In the secondary phase, the resultant latent component vectors were fused and fed as input vector to the DNN for optimizing the whole framework. But, it needs additional attributes like opinions, tags, text or semantic attributes of products for enhancing the suggestion efficiency.

An enhanced suggestion model [10] has been presented which comprises content-based, cooperative and hybrid filtering units. The tagging attributes were used for giving highly suitable suggestions on discussion sets. First, the semantic significance of tags was mined by WordNet lexical database and the tags were arranged in a hierarchical structure depending on their semantic significance. The hierarchical structure was applied to explore important posts in content-based filtering unit and the client's query was expanded by the corresponding semantic tags. Also, the implicit ratings of the clients were determined in the cooperative filtering unit by similarity measures. At last, the outcomes of such 2 units were fused in the hybrid filtering unit for suggesting the posts of the discussion set which were identical to the query of the active client. But, the performance of this model was not highly efficient.

A new deep learning ensemble suggestion model [11] has been designed which utilizes embeddings for defining clients and products to train non-linear latent components. Initially, the cold start challenge was solved by using side data about clients and products into a DNN. After that, the advantages of conventional MF schemes were retained by training latent components and constructing them to train non-linear latent components using embeddings. Also, the maximum

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prediction efficiency was achieved by the cyclical training fractions and decaying weights across epochs. But, it has high training and prediction time as well as it needs additional attributes for increasing the prediction accuracy.

A social suggestion model [12] has been developed depending on the reliable implicit correlations. The Dempster-Shafer theory was applied as an effective statistical method for computing the implicit correlations. Also, a novel measure was used for analyzing the reliability of estimations where unreliable estimations were recomputed by the neighborhood enhancement method. A confidence measure was utilized between the clients for identifying the inappropriate clients in the neighborhood group of a target client. At last, new reliable ratings were computed through eliminating the recognized inappropriate adjacent. But, its performance was not highly effective in terms of precision and recall.

An enhanced ride sharing framework [13] has been presented in which the riders were matched depending on a particular group of human behaviors using machine learning. Once the trip was finished, the client's opinion was observed and the major behaviors of riders were measured. The recorded and the measured behaviors were given to the Support Vector Machine (SVM) classifier to predict behaviors of new riders. But, the overall precision was not high and the SVM takes more time for training process.

A pattern-driven ensemble library suggestion model [14] has been designed which utilizes machine learning approaches for suggesting and assisting in the collection and weeding decision-making functionalities through mining and evaluating the client's feedbacks and ratings. But, it needs to analyze the client's desires and reviews for enhancing the prediction efficiency.

An enhanced intelligent suggestion model [15] has been designed which ensembles CF and K-means clustering. Also, particular client demographic attributes were applied to create the partitioned client profiles whilst products were clustered by genre attributes based on K-means. Then, clients were grouped according to their desires of products and the genres. Moreover, CF was employed to suggest products to an active client. On the contrary, it was difficult to decide the optimized clusters.

A deep learning-based technique [16] has been developed to accomplish a multi-criteria suggestion model. In this technique, deep auto-encoders were employed to utilize the non-trivial, nonlinear and secret correlations among clients about multi-criteria desires and provide extremely accurate suggestion. However, its precision was not effectively enhanced. The Grey-Sheep One-class Recommendation (GSOR) model [17] has been presented for constructing the precise estimation frameworks when considering normal and grey-sheep clients. In this model, different schemes such as one-class learning, outlier identification and unsupervised training were ensemble. Also, a new grey-sheep film suggestion was utilized. But, its accuracy was not effective and the effect of changing client desires on the suggestion model was not analyzed.

III. PROPOSED METHODOLOGY

In this section, the DIDPMF model is described briefly. The schematic representation of DIDPMF model is illustrated in Fig. 1. This DIDPMF comprises 3 primary steps:

- Information splitting: Primarily, the set of training data is partitioned into an optimized number of partitions for creating the fast parallel and distributed model.
- Learning step: After that, the learning task is carried out by the distributed predictive MF with DIPMI model for representing the desires, feedbacks and social context of all clients in the training dataset.
- Prediction step: Further, the rating prediction is devised as a regression problem and resolved by the fDNN for estimating the client's rating nature according to their feedbacks and social context for each item.

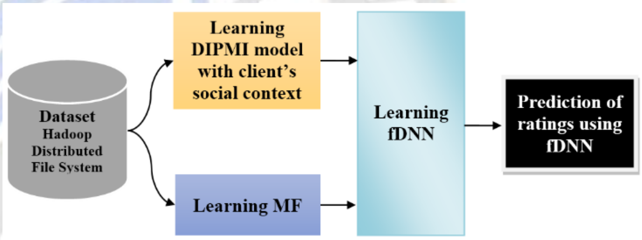

Figure 1. Schematic representation of DIDPMF model for rating prediction.

A. *Information Splitting*

First, the training set of data, D_{train} is partitioned into an optimized number of partitions which enables DIDPMF model to execute the fast parallel and distributed learning task. Assume N_p is the set of possible number of partitions and $Itvl(D_{train}, n_p)$ is the operation which characterizes the least computation interval required for learning according to the parameter n_p. So, the training set partitioning problem is represented by

$$n_p^* = \underset{n_p}{\operatorname{argmin}} \left(Itvl(D_{train}, n_p) \right), \forall n_p \in N_p$$

$$\text{s.t. } D_{train} = \left(D_{train}^{(1)} \cup \ldots \cup D_{train}^{(n_p^*)} \right) \quad (1)$$

In Eq. (1), n_p^* is the optimized number of partitions, $D_{train}^{(1)}$ is the partition.

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B. DIDPMF: Distributed Improved Deep Prediction with MF and FDNN

The main purpose of DIDPMF is taking the advantages of DIPMI [8] with MF and fDNN models for improving the recommendation quality. First, all identified ratings $r_{u,c,i} > 0$ in D_{train} are defined as attributes and labels. Then, the rating estimation is formulated as the regression dilemma. Let $= \{(x_j, y_j), j = 1, \dots, |N|\}$ be the D_{train} comprised of $|N|$ examples where $|N|$ is the quantity of non-zero client-item rating R. All $x_j \in \mathbb{R}^{\beta+1}$ and $y_j \in \mathbb{R}$ are the attributes of an information j i.e., formed representation and the label i.e., ground-truth rating, correspondingly.

Assume β denotes the number of MFs, the key intend is to learn β MF with DIPMI and the trained models are utilized to form the representation of each rating $r_{u,c,i}$ (defined by the user u and their social context c for an item i) in D_{train} as:

$$L(r_{u,c,i}) = (x_j, y_j)$$
$$x_j = \left(E_{u,c}^{(1)} W_i^{(1)}, \dots, E_{u,c}^{(\beta)} W_i^{(\beta)}, \hat{r}_{u,c,i}\right)$$
$$y_j = r_{u,c,i} \quad (2)$$

In Eq. (2), $L(\cdot)$ can define the ratings using the trained models, $\left(E_{u,c}^{(1)} W_i^{(1)}\right)$ and $\left(E_{u,c}^{(2)} W_i^{(2)}\right)$ indicate the latent components determined through the primary and secondary MF models, correspondingly. Also, $\hat{r}_{u,c,i}$ is the predicted rating of u based on their c for i. The fundamental statement behind (2) is to form the representation which signifies all ratings and use these representations by the fDNN learning which offers enhanced recommendations. So, the rating prediction problem is tackled by fDNN with the aid of pre-defined labels. The RF is a collection of decision trees which are trained according to the bagging. Once RF is trained, the learned framework is used for predicting the unknown preferences.

fDNN-based Learning and Prediction: The fDNN combines both random forest and DNN together for achieving efficient classification and high accuracy. As a result, an ensemble model i.e., employing random forest over DNN has the ability to output prediction results from all its base learners rather than a single predicted probability score. This fDNN has two modules: forest module and DNN module.

The forest module can learn the sparse representations from the given representations of client's desires, opinions and social context with the supervision of training outcomes whereas the DNN module can predict the ratings of a certain client. In the forest module, independent decision trees are constructed and then ensemble those trees to obtain the forest. The client rating prediction using fDNN learning is depicted in Fig. 2.

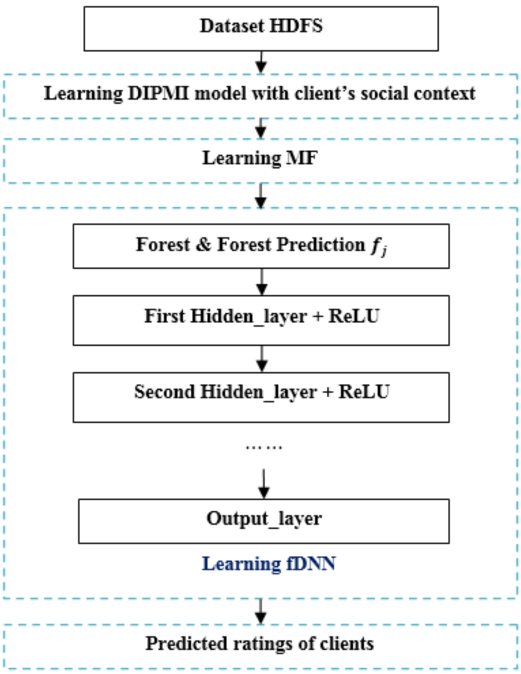

Figure 2. Flow diagram of rating prediction using fDNN learning.

In this fDNN model, a forest $\mathcal{F}$ is a collection of decision trees as:

$$\mathcal{F}(\theta) = \{\mathcal{I}_m(\theta_m)\}, m = 1, \dots, M \quad (3)$$

In Eq. (3), M is the total number of trees in the forest, $\theta = \{\theta_1, \dots, \theta_M\}$ is the parameters in $\mathcal{F}$. In random forests, θ includes splitting variables and their splitting values. In the attribute representation step, $\mathcal{F}$ is filtered by D_{train} which involves $y_j \in \mathbb{R}$ and $x_j \in \mathbb{R}^{\beta+1}$. By using the filtered forest, for any observation $x_j, j = 1, \dots, N$, the prediction from each tree in $\mathcal{F}$ is obtained as:

$$f_j = f(x_j; \theta) = \left(T_j(x_j; \theta_1), \dots, T_M(x_j; \theta_M)\right)^T \quad (4)$$

In Eq. (4), $T_M(x_j; \theta_M) = \hat{y}_{jm}$ is the binary prediction of observation x_j given by $\mathcal{I}_m$. Then, the obtained new attributes are fed into the DNN which has g hidden layers and s standard structure as:

$$Pr(y|F, \Psi) = l(Z_{out} W_{out} + b_{out}) \quad (5)$$
$$Z_{out} = \sigma(Z_g W_g + b_g) \quad (6)$$
$$Z_{k+1} = \sigma(Z_k W_k + b_k) \quad (7)$$
$$Z_1 = \sigma(F W_{in} + b_{in}) \quad (8)$$

In Eq. (5), Eq. (6), Eq. (7), Eq. (8), $F = (f_j, \dots, f_M)^T$ is the forest matrix i.e., attribute vectors with N examples and M tree predictions, Ψ is all the learning variables in the DNN, Z_{out} and $Z_k, k = 1, \dots, g -$ Here, $F = (f_j, \dots, f_M)^T$ is the forest matrix i.e., attribute vectors with N examples and M tree predictions, Ψ is all the learning variables in the DNN, Z_{out} and $Z_k, k = 1, \dots, g - 1$ are hidden neurons with corresponding weight matrices W_{out}, W_k and bias vectors

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b_{out}, b_k. The dimensions of Z and W depend on the number of hidden neurons h_{in} and $h_k, k = 1, \ldots, g$ including the input dimension M and the number of labels h_{out}. Normally, the hidden neurons decreases from the input layer, namely $h_{in} = M > h_1 > h_2 \ldots > h_{out}$. Also, $\sigma(\cdot)$ is the activation function number i.e., $(\sigma_{ReLU}(y) = max(y, 0))$ and $l(\cdot)$ is the softmax function can be rewritten as Eq. (9), Eq. (10), Eq. (11), Eq. (12)

$$p_j = l(\mu_{j1}) = \frac{e^{\mu_{j1}}}{e^{\mu_{j0}} + e^{\mu_{j1}}} \tag{9}$$

Where $p_j := P(y_j = 1|f_j)$ (10)

$$\mu_{j0} := \left[z_j^{(out)}\right]^T w_0^{(out)} + b_j^{(out)} \tag{11}$$

$$\mu_{j1} := \left[z_j^{(out)}\right]^T w_1^{(out)} + b_j^{(out)} \tag{12}$$

The learning variables to be computed in the DNN are all weights and biases. This fDNN can be learned by the Stochastic Gradient Descent (SGD)-based algorithm through minimizing the cross-entropy error value as:

$$\mathcal{L}(\Psi) = -\frac{1}{N}\sum_{j=1}^{N}\{y_j log(\hat{p}_j) + (1 - y_j) log(1 - \hat{p}_j)\} \tag{13}$$

In Eq. (13), $\hat{p}_j$ is the fitted value of p_j. Therefore, the ratings of different clients are predicted effectively to appropriately recommend the items.

IV. EXPERIMENTAL RESULTS

In this section, the DIDPMF model is executed in MATLAB 2017b to analyze its efficiency and compare to the existing models include DIPMF [8], DIPMI [8], DPMF [7], DPMI [7] and DPM [7] models. In this experiment, the products from Trip Advisor and Amazon datasets are used to reorganize and suggest the products to the clients depending on estimation of its rating characteristics. The comparison analysis is conducted in terms of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Quality (Q) and Confidence Level (CL).

A. Dataset Description

Trip Advisor Dataset: It is acquired from University of California-Irvine (UCI) and encompasses 2 datasets: car and restaurant ratings. Car dataset involves the absolute rating of car models for 2007, 2008 and 2009. For each model year, almost 250 various cars and nearly 42230 ratings are involved. The structure of this dataset includes car brand, year, amount of ratings, power, interior, exterior, design, efficiency, quality, serviceability, pleasure and total reviews. Restaurant dataset involves the absolute ratings of hotels in 10 places and almost 700 hotels are found in each place. So, it has about 259000 ratings. The structure of this dataset includes hotel's ID, name, website, address, locality, country, zip code, amount of ratings, neatness, accommodation, facility, price, affordability and total reviews.

Amazon Dataset*:* It encompasses 143.7 million ratings of items covering between May 1996 and July 2014. The subcategories include articles, TVs, electronics, movies, fashion, appliances, etc. In this analysis, only movies & TV subcategory is decided due to the high processing duration to evaluate an entire dataset. All Amazon subclass dataset has 2 different subcategories:

- The review set includes the reviewer's ID, name, item ID, review text, item rating, summary, and time of the rating.
- The metadata includes item ID, name, cost, website of item image, related items, sales order details, model, and the item categories.

These datasets are managed through mining the appropriate information and the ratings of particular clients and items in different periods.

B. Evaluation Metrics

RMSE and MAE: These metrics are considered to determine the accurateness of estimation.

$$RMSE = \sqrt{\frac{\sum_{u\in U, c\in C, i\in I}(r_{u,c,i} - \hat{r}_{u,c,i})^2}{n}} \tag{14}$$

$$MAE = \frac{\sum_{u\in U, c\in C, i\in I}|r_{u,c,i} - \hat{r}_{u,c,i}|}{n} \tag{15}$$

In Eq. (14), Eq. (15), n is the number of ratings, $r_{u,c,i}$ is the ground-truth rating shared by u and c to i and $\hat{r}_{u,c,i}$ is the estimated rating. The least error range signifies a better accurateness of estimation.

Quality *(Q):* It determines the suggestion efficiency by

$$Q = \sum_{i=1}^{Z} RP_i \tag{16}$$

In Eq. (16), RP_i is the score of i with a price P if i is in the high range or 1 if i is in the smaller range and Z is the overall price of i decided by u. The maximum Q range specifies the highest suggestion efficiency.

Confidence Level (CL): It is the period around the estimated rating where the ground-truth rating lies within a constant CL i.e., 95%. The least estimated period signifies the highest confidence of the rating estimation. It is considered to analyze the rating confidence.

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C. RMSE

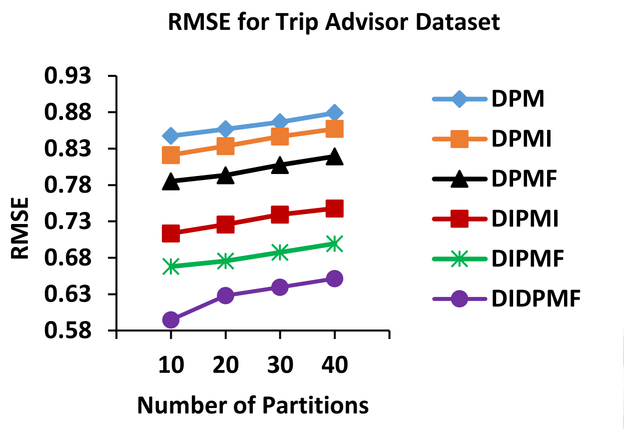

Figure 3. RMSE vs. number of partitions for trip advisor dataset.

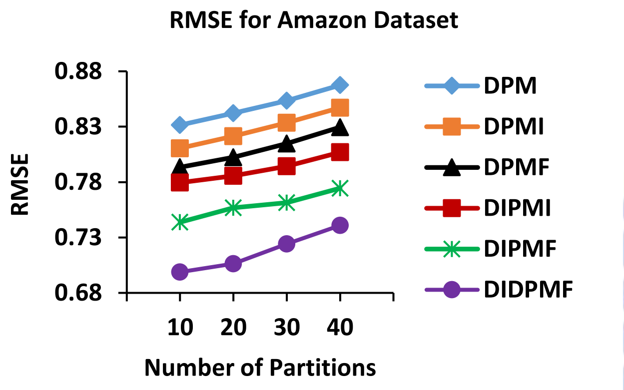

Figure 4. RMSE vs. number of partitions for amazon dataset.

The RMSE values for different recommender system models on Trip Advisor and Amazon datasets under various amounts of partitions are illustrated in Fig. 3 and Fig. 4, accordingly. It notices that when raising the amount of partitions in the training set of data, the RMSE of DIDPMF on both dataset is smaller than all other rating prediction models.

D. MAE

The MAE values for different recommender system models on Trip Advisor and Amazon datasets under various amounts of partitions are illustrated in Fig. 5 and Fig. 6, accordingly. It notices that when raising the amount of partitions in the training set of data, the MAE of DIDPMF on both dataset is smaller than all other rating prediction models.

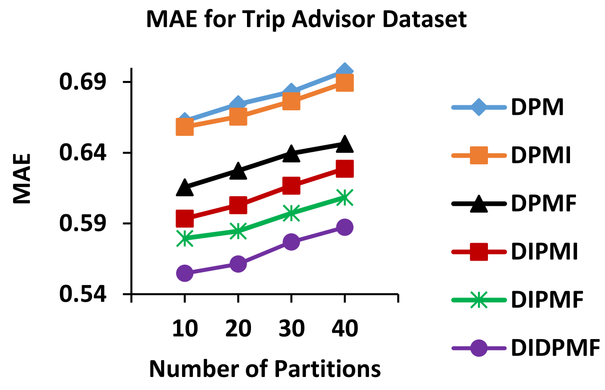

Figure 5. MAE vs. number of partitions for trip advisor dataset.

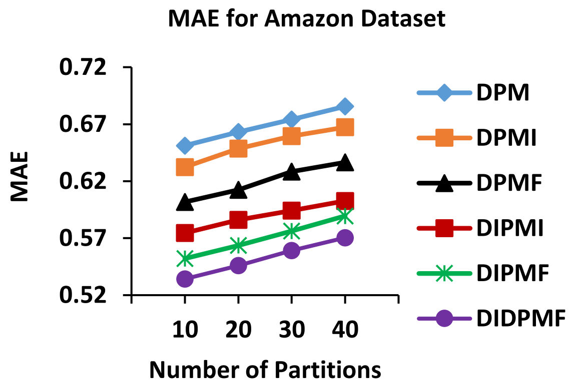

Figure 6. MAE vs. number of partitions for amazon dataset.

E. Quality

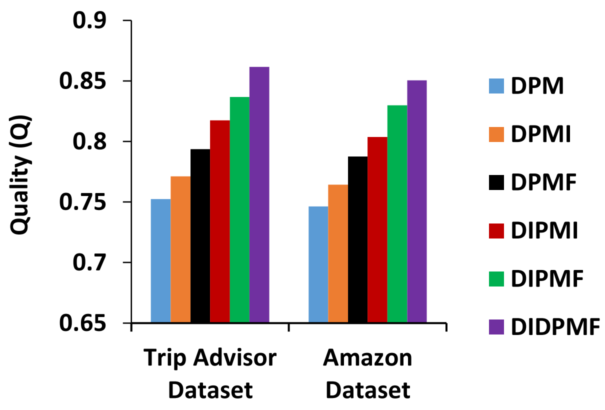

Figure 7. Quality vs. datasets.

The Q ranges for different recommendation system models on both Trip Advisor and Amazon datasets are portrayed in Fig. 7. It observes that the Q of DIDPMF on both datasets is greater than all other rating prediction models. So, it is obvious that the prediction or recommendation efficiency is enhanced by the DIDPMF compared to all other existing models.

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F. Confidence Level

Fig. 8 shows the 95% CL ranges for various recommender system models on both Trip Advisor and Amazon datasets. It addresses that the 95% CL of DIDPMF on both datasets is lesser compared to all other rating prediction models. So, it is concluded that the confidence of estimating ratings using DIDPMF is increased than the other existing models.

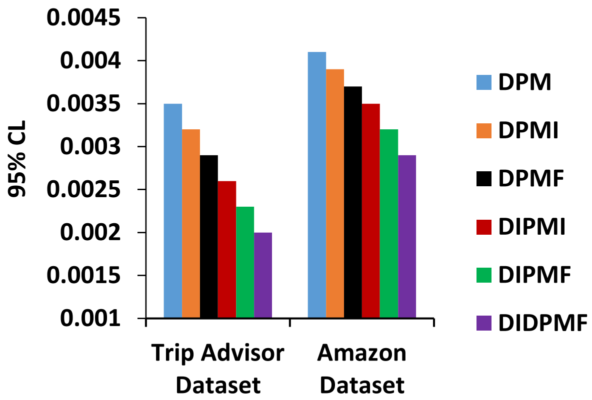

Figure 8. 95% CL vs. datasets.

V. CONCLUSION

In this paper, a DIDPMF model is proposed in which a forest attribute extractor is ensemble with the DNN for extracting the sparse attribute correlations from an extremely large attribute space. It consists of forest and DNN modules. The forest module is employed as an attribute extractor to extract the sparse representations from the given raw input data with the supervision of learning outcomes. First, independent decision trees are constructed and then ensemble those trees to obtain the forest. After, this forest is fed to the DNN module which acts as a learner to predict the individual's ratings with the aid of novel attribute representations. To conclude, the findings proved that the DIDPMF achieves a better efficiency in terms of RMSE, MAE, quality and 95% CL compared to the other existing recommender systems.

REFERENCES

[1] N. Yin, "A big data analysis method based on modified collaborative filtering recommendation algorithms," Open Physics, vol. 17(1), pp. 966-974, 2019.

[2] M. Gao, J. Zhang, J. Yu, J. Li, J. Wen, and Q. Xiong, "Recommender systems based on generative adversarial networks: a problem-driven perspective," Information Sciences, vol. 546, pp. 1166-1185, 2021.

[3] M. Dhamecha, K. Dobaria, and T. Patalia, "A survey on recommendation system for bigdata using mapreduce technology," IEEE 3rd International Conference on Computing Methodologies and Communication, pp. 54-58, 2019.

[4] V. K. Sejwal, and M. Abulaish, "CRecSys: a context-based recommender system using collaborative filtering and LOD," IEEE Access, vol. 8, pp. 158432-158448, 2020.

[5] Z. Fayyaz, M. Ebrahimian, D. Nawara, A. Ibrahim, and R. Kashef, "Recommendation systems: algorithms, challenges, metrics, and business opportunities," Applied Sciences, vol. 10(21), pp. 1-20, 2020.

[6] M. Huang, J. OuYang, C. Wu, and L. Bo, "Collaborative filtering based on orthogonal non-negative matrix factorization," Journal of Physics: Conference Series, IOP Publishing, vol. 1345(5), pp. 1-7, 2019.

[7] B. A. Hammou, A. A. Lahcen, and S. Mouline, "An effective distributed predictive model with matrix factorization and random forest for big data recommendation systems," Expert Systems with Applications, vol. 137, pp. 253-265, 2019.

[8] M. Kavitha, and S. Subbaiah, "Big-data recommendation system using distributed improved predictive framework with matrix factorization and random forest," International Journal of Intelligent Engineering & Systems, vol. 15(4), pp. 447-457, 2022.

[9] R. Wang, H. K. Cheng, Y. Jiang, and J. Lou, "TDCF: a two-stage deep learning based recommendation model," Expert Systems with Applications, vol. 145, pp. 1-10, 2019.

[10] M. Riyahi, and M. K. Sohrabi, "Providing effective recommendations in discussion groups using a new hybrid recommender system based on implicit ratings and semantic similarity," Electronic Commerce Research and Applications, vol. 40, pp. 1-13, 2020.

[11] R. Kiran, P. Kumar, and B. Bhasker, "DNNRec: A novel deep learning based hybrid recommender system," Expert Systems with Applications, vol. 144, pp.1-32, 2020.

[12] S. Ahmadian, N. Joorabloo, M. Jalili, Y. Ren, M. Meghdadi, and M. Afsharchi, "A social recommender system based on reliable implicit relationships," Knowledge-Based Systems, vol.192, pp. 1-17, 2020.

[13] G. Yatnalkar, H. S. Narman, and H. Malik, "An enhanced ride sharing model based on human characteristics and machine learning recommender system," Procedia Computer Science, vol. 170, pp. 626-633, 2020.

[14] M. Rhanoui, M. Mikram, S. Yousfi, A. Kasmi, and N. Zoubeidi, "A hybrid recommender system for patron driven library acquisition and weeding," Journal of King Saud University-Computer and Information Sciences, pp. 1-11, 2020.

[15] A. F. O. U. D. I. Yassine, L. A. Z. A. A. R. Mohamed, and M. Al Achhab, "Intelligent recommender system based on unsupervised machine learning and demographic attributes," Simulation Modelling Practice and Theory, vol. 107, pp. 1-16, 2021.

[16] Q. Shambour, "A deep learning based algorithm for multi-criteria recommender systems," Knowledge-Based Systems, vol. 211, pp.1-13, 2021.

[17] R. Alabdulrahman, and H. Viktor, "Catering for unique tastes: targeting grey-sheep users recommender systems through one-class machine learning," Expert Systems with Applications, vol. 166, pp. 1-12, 2021.