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ORIGINAL PAPER

Multimodal trust based recommender system with machine learning approaches for movie recommendation

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Abstract Recommender system (RS) are a type of suggestion to the information overload problem suffered by user of websites that allow the rating of particular item. The movie RS are one of the most efficient, useful, and widespread applications for individual to watch movie with minimum decision time. Many attempts made by the researchers to solve these issues like watching movie, purchasing book etc., through RS, whereas most of the study fails to address cold start problem, data sparsity and malicious attacks. This study address these problems, we propose trust matrix measure in this paper, which combines user similarity with weighted trust propagation. Non cold user passed through different models with trust filter and a cold user generated an optimal score with their preferences for recommendation. Four different recommendation models such as Backpropagation (BPNN) model, SVD (Singular Value Decomposition) model, DNN (Deep Neural Network model) and DNN with Trust were compared to recommend the suitable movie to the user. Results imply that DNN with trust model proved to be the best model with high accuracy of 83% with 0.74 MSE value and can be used for best movie recommendation.

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Keywords Collaborative filtering · Singular value decomposition · Back propagation neural network · Deep neural network · Trust

1 Introduction

Rapid growth of technology leads to tremendous increase in data due to web services, e-commerce domain, movie, music and jokes etc. To provide right information out of the information pool is a major problem. Recommender system retrieves the classical information based on the historical behaviour of the user rather than answering any user's query. The different flavours of recommendation techniques can be named as content enabled recommendation approach, collaborative recommendation approach, knowledge-inbuilt recommendation approach and utility as well as demographic recommendation filter techniques. Out of which collaborative, content based and combined technique i.e. hybrid techniques are preferred to construct recommendation system (RS). The content enabled recommendation [22] approach investigates the dissimilar attributes of the items and advocates a like product to the lively users. Collaborative recommendation approach finds the similarity index for the users by keeping a close eye on their prior ratings with the supposition that the consumers making analogous choices in the earlier period must do related choices in the upcoming times [4, 11]. The demographic as well as knowledge inbuilt recommendation system is about region-specific data filtration and explicit item-specific data filtration respectively [20]. The Hybrid Recommendation system can be formed by taking an assembly of one or more flavours of RS approaches.

The most widely used recommender system is the collaborative RS. However it suffers from different problems such as cold-start (for new user as well as for new items there is no recommendation list), data sparsity (user-item matrix has less number of ratings) [18], malicious attacks (ratings of users is copied by other user leading to soaring similarity between the users) and Gray-sheep problem (user's taste is unique, hence the recommendation system disables to produce recommendation) [9]. Because of the restrictions and challenges of collaborative (CF) recommendation, instead of similarity based user, trust and resemblance between the users are taken into consideration for better recommendation. In the absence of data rating, social relationship between the users can be considered as a trust factor between them [16, 17]. Trust among the users is of two types. Implicit trusts [3, 7, 12] specify the trust among the users and can be calculated based on the information available on the data set. Explicit trust specifies the user's trust provided by the user. Explicit trust is difficult to achieve due to data sparsity or for no information availability. Hence there are different metrics available which used to calculate the implicit trust. For the similar couple of clients such trust can have a negative impact by producing a high value of trust as a trust measure. Such problem in implicit trust can be improved by designing a metric so that the correct trust between the similar users can be estimated [5, 6].

Users are allowed to state how much they consider trustworthy to other user. In the context of recommender systems, this judgement is related to how much they consider the ratings provided by a certain user as valuable and relevant. This trust calculation can easily be expressed in terms of a trust network and the trust metric is used as a connecting edge between two users.

In collaborative filter, searching for a trustable users can be done by using trust propagation over the trust network. The items appreciated by these trusted users are then recommended to the active user, termed as Trust-aware Recommender System. In the ensemble model four different machine learning algorithms such as: Back propagation, SVD (Singular Value Decomposition), Deep Neural Network and DNN with trust are embedded. Popularity based recommendation model have been used to resolve the cold user problem normally occurred in CF.

2 Related work

The eminence of the recommendation system can be improved through different methodologies implemented on collaborative filter. It is basically of two ways. Firstly, Traditional recommender systems and Trust-worthy recommender systems based on trust between users.

2.1 Traditional collaborative filtering based recommender systems

The two classes of CF algorithms are memory based and model based algorithms. Recommendations based on complete user profile database known as Memory based algorithms while model based algorithms trained a model with previous history of user profile and recommend accordingly. Goldberg and Nichols [9] explains how collaborative filtering algorithms implemented in practical aspects to identify similar users in an information tapestry. Ungar and Foster [25] represents variations of K-means clustering and Gibbs Sampling on model parameters to estimate the model and compare with statistical model of collaborative filtering. Later, in Konstan et al. [13] automate the grouping of news articles in Usenet using CF too. Goldberg et al. [10] recommend jokes to the user and books by Amazon using CF recommender systems based on Jester system. On the basis of user preference, CF system provides unexpected qualitative information to the user. But cold start, data Sparsity and Gray sheep problem is significant in CF systems. Accuracy of the CF system decreases due to data sparsity. Nagpal et al. [24] evade the data sparsity problem for feature selection of biomedical data using Gravitational search algorithm. Gupta and Hagpal [12] discussed when the taste of one user doesn't match with others, the CF system disable to produce recommendation in support to Gray sheep problem.

2.2 Trust-worthy recommender systems

Concentration has been given towards incorporate trust in recommended system because of the problem of sparsity and malicious attacks. In traditional CF. Trust is an agreement between choices of the friends and colleagues upon the user. Evaluation of trust information tries to overcome the problems in CF. Implicit trust mined out from the similarity of the users while explicit trust value has been given by the user exclusively. Donovan and Smyth [4] discussed about the effectiveness of trusted users for recommendation. They proposed quality recommendations using Resnick formula on the basis of profile level and item level implicit trust. Golbeck and Rovideskey [8] evaluates the trust value for a movie recommendation by using the Tidal Trust algorithm. By means of nearest trust path, this algorithm tries to find the scorings of all users made by the target user. Lathia et al. [14] proposed trusted k-nearest recommenders (KNR) algorithm to trust information between the users and tried to remove the drawbacks of traditional CF. Massa and Bhattacharjee [16] recommended common items using the explicit trust data from the users to conciliate the sparsity of the ratings. Massa and Avesani [15] proposed a novel approach to reduce the data sparsity and cold start problem for explicit recommendation using trust metrics and its propagation. Shamri and Bharadwaj [2] introduced different recommendation policies by exploring both trust and distrust. Computing weighted trust metrics and implementation of Fuzzy focused on to generate better recommendations. The above-mentioned algorithms use trust relationship among users and the similarity between users in addition it neglect the trust propagation mechanism between users, so it can't well solve the problem of data sparsity and Gray sheep problem. Keeping the problems occurred in CF, we considered both trust and similarity between users.

3 Proposed model of recommendation

The proposed model recommends the movie to the trusted user on the basis of implicit trust value and different machine learning approaches (see Fig. 1).

Collaborative filtering handles the similarities between the users and items to perform recommendations. It continuously finds the relationships between the users and in-turns does the recommendations. The two most well-known distinct approaches of CF are (1) memory-based approach in which, calculating the similarities between users/items based on user-item rating pairs and (2) model-based approach use some sort of machine learning algorithm to estimate the ratings. The main challenges in the memory based techniques are data sparsity and scalability, where Model-based algorithms developed a model based on user rating and provides item recommendation [21]. The Matrix Factorization is the most common model based technique to find the embeddings or features that makes up the interest of a particular user. Different machine learning techniques such as Singular Value Decomposition (SVD), Back propagation, Deep Neural Network (Auto encoder) model were implemented to predict the accurate recommendation.

3.1 Matrix factorisation

Matrix factorization is a way to generate latent features when multiplying two different kinds of entities. Application of matrix factorization [3, 23] in CF is to identify the relationship between items' and users' entities. With 95% sparsity in users' ratings, the recommendation model provides high computational complexity with low accuracy. Matrix factorization is a process, where the actual users' rating matrix is divided into two feature (user and item) matrices in such a way that multiplication of the new two

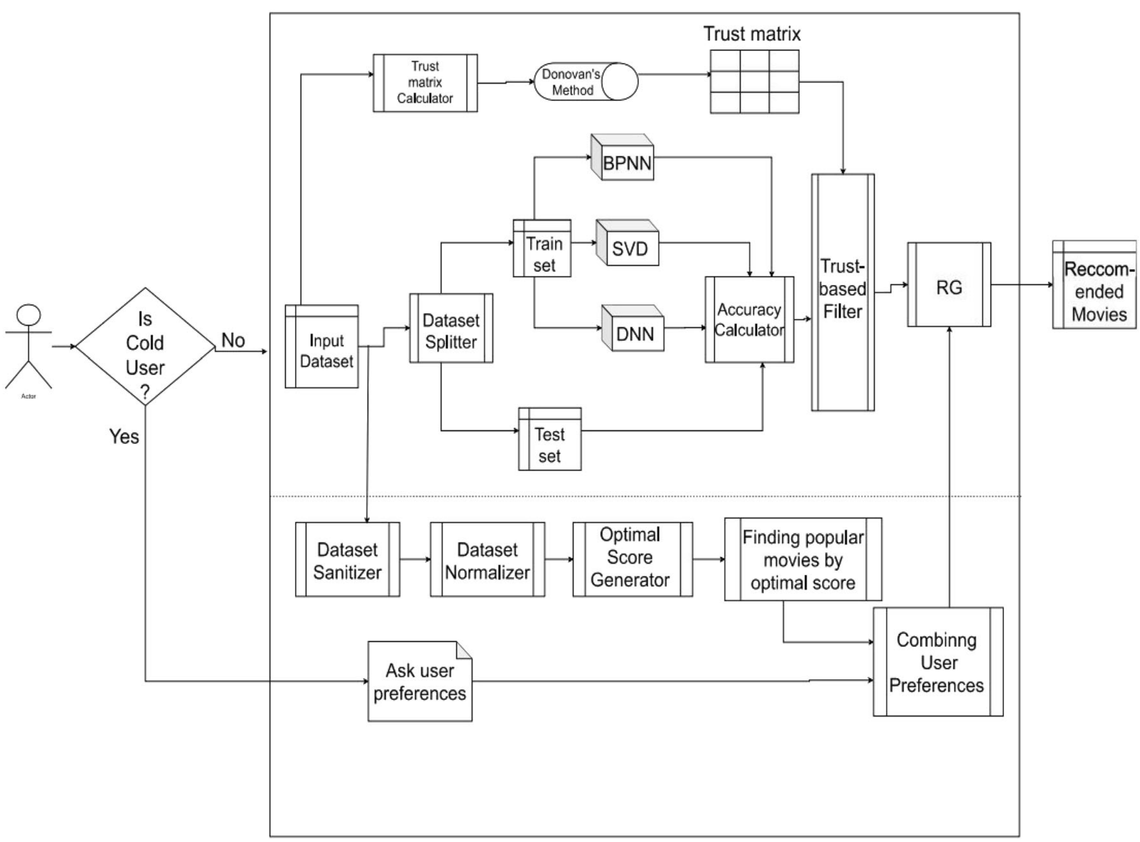

Fig. 1 Proposed model architecture

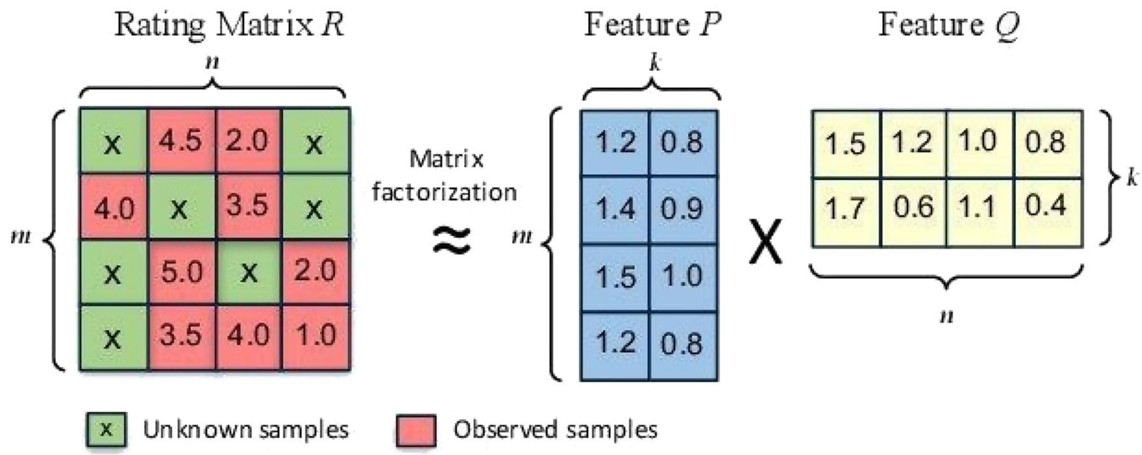

Fig. 2 Matrix factorisation

matrices will give the actual matrix. The predicted matrix has similar output with the true values, and the 0 ratings in actual matrix are replaced with the prediction based on the similar users' preferences (see Fig. 2).

Matrix factorisation is easy to implement, potentially interpretable and requires less query time. However this cannot capture complex relation in data due to linear model.

3.2 Singular value decomposition (SVD)

Singular value decomposition (SVD) is a factorization of a real or complex matrix in to

$$A = USV^T \tag{1}$$

where U is an m $\times$ x matrix, V is an n $\times$ x matrix and S is an x $\times$ x diagonal matrix with non-negative values. SVD proposes prediction of the rating of an item for a target user that is not yet rated and if the predicted rating is high then that item will be recommended to the target user. To generate a recommendation for a target user feature vector of the target user from the newly computed user-item rating matrix has been considered and select high predicted rating items. SVD is a very efficient algorithm and it is applicable for big metrics and it performs very well for most of the dataset. But for strongly non-linear data SVD is not worked well. The accuracy of the model can't be improved because of single mathematical formula implemented in it, where we can change only the parameter (number of features).

3.3 Backpropagation neural network (BPNN)

Neural networks are machine learning algorithms used to model complex patterns in datasets. The layers of inter-connected functional units called nodes or neurons are non-linear activation functions. In this model the input layer of the network is an embedding layer (a fully connected layer represents the sparseness to a dense vector) where the user and item feature vector are input to it. The internal weights of input signals modified by a given function to produce predictive output (see Fig. 3).

- Embedding of user features, size:- $nUsers \times nFeatures$
- Embedding of item features, size:- $nItems \times nFeatures$

Both of these embedding will be filled with random values [1, 1].

User Feature embedding will supply the weights for $user_i$, which will be placed between input layer and hidden layer. Item Feature embedding will supply the weights for $item_i$, which will be placed between hidden layer and output layer. The network weights were updated according to the error back propagated with number of epochs while trained and test the network. The network updated itself in a way of stochastic gradient descent method. The dot product of randomly generated user-item feature vector provides the predictive rating as an output.

3.4 Deep neural network (DNN)

DNN is the multiple neural building blocks that can be composed in to a single differentiable and trained the network end to end [19]. The interesting features are end to end differentiability and provide suitable inductive bias catered to the input data. Data complexity and large training samples leads to reasonable performance gain (see Fig. 4).

The deep learning method tried to predict the rating of an item for an active user and recommend an item to a user accordingly. The embedding layer receives the user-item feature matrix as an input. The dot product of two feature matrices are passed through dense hidden layer in which,

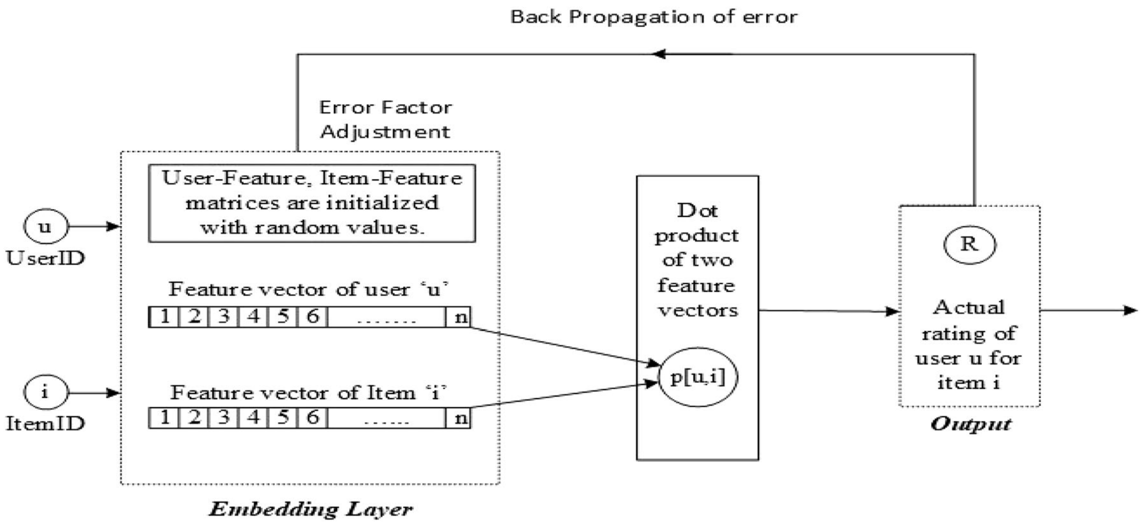

Fig. 3 Back propagation neural network model architecture

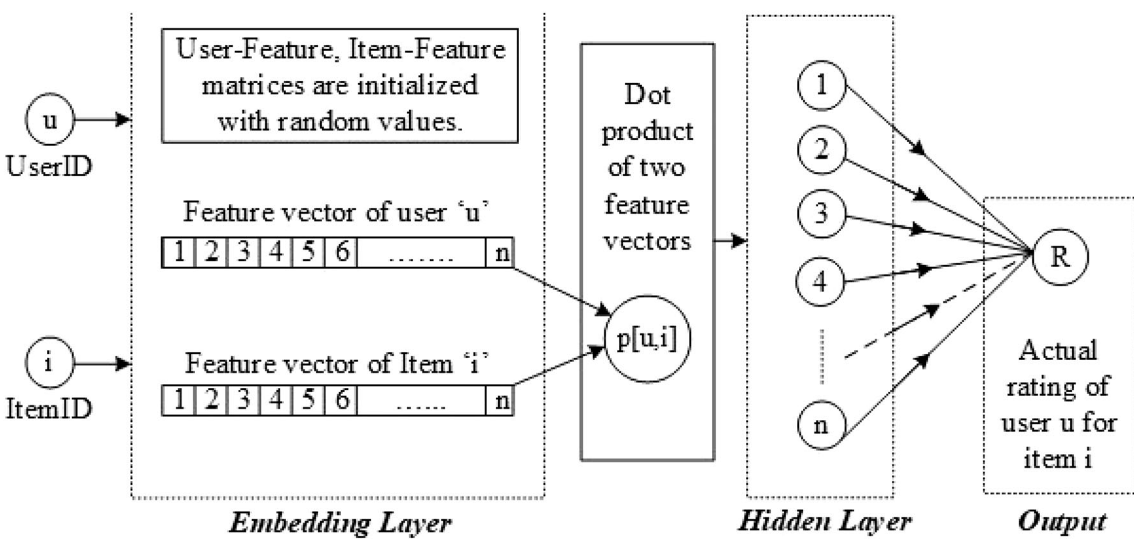

Fig. 4 Deep neural network model architecture

number of nodes in the layer is equal to the number of features. Accuracy of the model is measured through MSE (Mean square error).

3.5 Trust based filter

In CF, Consumer searches for the information and producer provides the information. The technical hitches of CF systems can be dealt with trust properties. The trust is assessed as readiness to accept the truth in a client on the basis of expertise and performance in a particular time. A trust system is considered as a network of interfacing peers. The communication between two domestic entities is considered as an end product of building the trust association with an additional entity by the prescribed representations of trust. According to Donovan and Smyth [4], Local trust and Global trust are two important distinction of trust metric. Without peer dependency, computation of a single score termed as Global Trust. Local trust metric provides personalized scores, means it suggests trustable peer. Predicted rating for an item i and consumer c, can be evaluated based upon producer profiles, associated with their individual average recommendations according to similarity with the consumer. Resnick's [4] standard prediction rating will be

$$c(i) = \bar{c} + \frac{\sum_{p \in P(i)} (p(i) - \bar{p}) * sim(c,p)}{\sum_{p \in P(i)} |sim(c,p)|} \tag{2}$$

For consumer profile c, $c(i)$ is the rating to be predicted for the item i and for producer profile p, $p(i)$ is the rating for the item i. c and p are the mean ratings of c and p respectively. The similarity between profiles c and p were measured by Pearson's correlation coefficients. The contribution to the rating prediction of a partner to its target user depends on the level of similarity between them given by Resnick. High similarity contributes more to the system in prediction of rating. $Trust^p$, the profile-level trust [4] is the percentage of correct recommendations that the producer has contributed.

$$Trust^p = \frac{|CorrectSet(p)|}{|RecSet(p)|} \quad (3)$$

where correct recommendation set is

$$Correct(i, p, c) \iff |p(i) - c(i)| < \epsilon \quad (4)$$

The difference of rating greater than some threshold value will be *correct* (*i, p, c*) recommendation and the whole recommendations for a producer is ***RecSet*(*p*)**.

Trusted based recommendation is filter decides the trustworthy profiles to participate in the prediction process. The modified version of Resnick's formula [4] allows producer profiles whose trust value exceeds some predefined threshold to participate in the recommendation process. The standard Resnick method applied to the most trustworthy profiles given (Eq. 5).

$$c(i) = \bar{c} + \frac{\sum_{p \in P^T(i)} (p(i) - \bar{p}) * sim(c, p)}{\sum_{p \in P^T(i)} |sim(c, p)|} \quad (5)$$

$$P^T(i) = \{p \in P(i) : Trust^p(p, i) > T\}$$

In a recommender system, trust values for producers can be annulled from the similarity measure between users and the variation of predicted rating and the actual rating.

In the proposed model an active user is being tested for cold user. Not being a cold user, trust between the intended users with other users in the system was calculated using Donovan's trust formula. Performance of all referred models being calculated and combined with trust value produced for the recommendation. For a cold user, Optimal Score Generator generates a score based on the rated movies and sorted in a descending order.

$$score = (timestamp / \max(timestamp)) \times z\_score$$

High order optimal score along with user preferences recommends the exact movie.

4 Result and discussion

In this section all the outputs and results of the above-mentioned models, processes and comparisons were given.

4.1 SVD model

In this model the input dataset is in user-item rating matrix. There are 610 number of users and 9724 number of items with 100,837 ratings. All the non zero value were replaced by predicted rating value of this model (see Fig. 5).

4.2 BPNN model

Loss (MSE) vs. Epoch graph: To calculate training loss and validation loss, mean square error (MSE) method is used. Backpropagation model gets over fitted over the training data, and the overall performance on the test data turn out very poor (see Fig. 6).

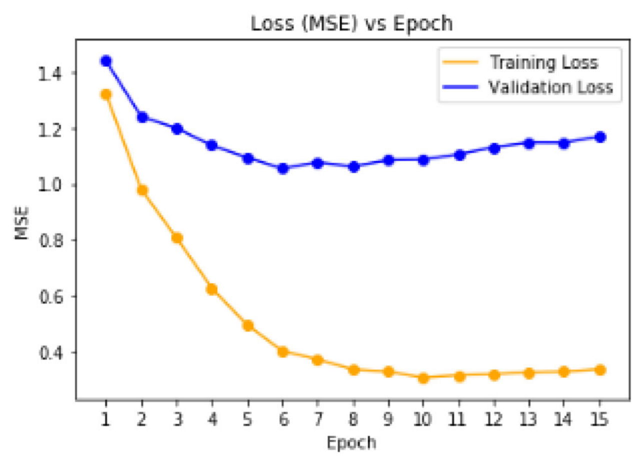

Fig. 6 Loss function of BPNN model

Fig. 5 Prediction of rating in SVD model

	1	2	3	4	5
0	4.000057	3.431818	4.000259	2.357143	3.071429
1	3.921763	3.436207	3.256481	2.357143	3.069633
2	3.920930	3.431818	3.259615	2.357143	3.071429
3	3.920097	3.431818	3.259615	2.357143	3.071429
4	4.001723	3.431818	3.253348	2.358721	3.068735
5	3.918431	3.998810	4.999970	3.000141	4.999996
6	4.500639	3.431818	3.259615	2.357143	3.071429
7	3.907604	3.999688	3.261705	2.352409	3.075020
8	3.921763	3.431818	3.259615	2.357932	3.070531
9	3.920930	3.431818	3.259615	2.357143	3.071429

10 rows × 9724 columns

4.3 Deep neural network model

Based on a target user, K-nearest neighbour to find out k most similar user and use their top rated movies for the recommendation. This can be shown in feature map (see Figs. 7 and 8).

4.4 Trust computation

Producer–consumer trust matrix is calculated using Donovan's trust method from consumer-rating matrix and user-feature matrix (see Fig. 9).

In trust computation diagonal cells as a consumer can't rely upon its own rating producing power. So, these diagonal cells have been replaced with 'Nan' value.

It has been found that, the MSE (Mean Square Error) values are decreasing for Back propagation, SVD and DNN model respectively. When trust has been incorporated with DNN the MSE value has improved (see Fig. 10).

5 Conclusion and future work

The recommendation model is being developed using different machine learning techniques and then used trust-based filtering to recommend with more accuracy. Accuracy measured in BPNN (41%), SVD (69%) and DNN (78%). The loss values of Backpropagation and DNN model were compared and validation loss of DNN with trust (83%) resulted better. Since Cold user has always been a potential problem of CF, high value of optimal score recommend better. Different bio inspired optimization techniques can be implemented on CF, Content based and Demographic based filtering and their performance can be compared for a better recommendation in future.

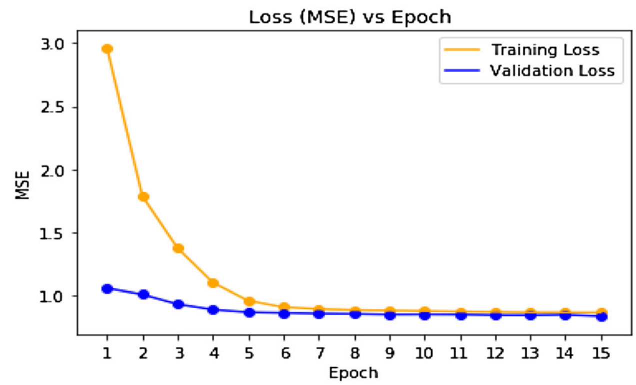

Fig. 7 Loss function of DNN model

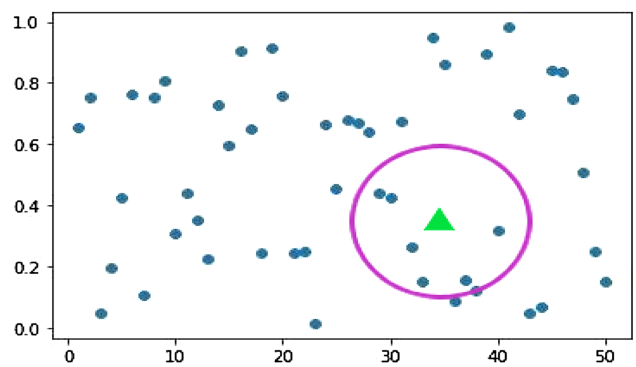

Fig. 8 Feature map of DNN model

Fig. 9 Trust matrix of Donovan's method

UserID	1	2	3	4	5	6	7
1	Nan	0.293103	0.025862	0.081897	0.073276	0.064655	0.081897
2	0.241379	Nan	0.034483	0.172414	0.172414	0.172414	0.137931
3	0.025641	0.102564	Nan	0.051282	0.051282	0.025641	0.102564
4	0.148148	0.273148	0.027778	Nan	0.069444	0.078704	0.111111
5	0.090909	0.272727	0	0	Nan	0.113636	0.181818
6	0.073248	0.27707	0.082803	0.133758	0.203822	Nan	0.280255
7	0.217105	0.230263	0.092105	0.118421	0.125	0.131579	Nan
8	0.042553	0.255319	0	0.021277	0.06383	0.042553	0.340426
9	0.130435	0.26087	0.086957	0.065217	0.086957	0.065217	0.152174

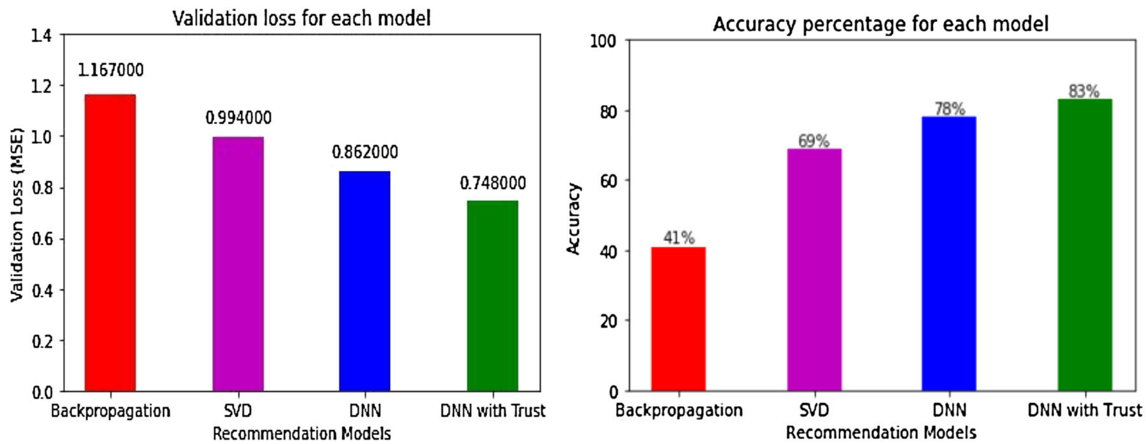

Fig. 10 Performance measure of proposed model

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