Novel Approach of Neural Collaborative Filter by Pairwise Objective Function with Matrix Factorization

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Abstract

The concept of deep learning is used in the various fields like text, speech and vision. The proposed work deep neural network is used for recommender system. In this work pair wise objective function is used for emphasis of non-linearity and latent features. The GMF (Gaussian matrix factorization) and MLP techniques are used in this work. The proposed framework is named as NCF which is basically neural network based collaborative filtering. The NCF gives the latent features by reducing the non-linearity and generalizing the matrix. In the proposed work combination of pair-wise and point wise objective function is used and tune by using the concept of cross entropy with Adam optimization. This optimization approach optimizes the gradient descent function. The work is done on 1K and 1M movies lens dataset and it is compared with deep matrix factorization (DMF).

Keywords: NCF, Gaussian, movielens

1. Introduction

Now it is the time when we have a large collection of useful information related to the products and services on the internet. Recommender system plays an important role in the websites and online services related to the e-commerce and video streaming. Recommendation system used to provides most appropriate product or services to the user related to their interest and choices. It is basically works as information filtering system on the basis of ranking and rating given by the users to the product on the website [1]. Recommendation is mainly based on the feedback and interest of users.

It is also an effective tool for personalization because it suggests the best thing according to the taste. This process is known as collaborative filtering. CF mainly predicts the interest of a particular user on the basis of similarity with past products selection. Rating is one of the effective methods used in collaborative filtering to extract the information from them [2].This approach is also differentiated into two types that are Memory-Based and Model Based. Matrix factorization is a technique of collaborative filtering approach which learns a latent space to represent a user or an item becomes a standard model for recommendation due to its flexibility and reliability. Latent space is basically predicts the personalized ranking over a set of items for each individual user with the similarity among the users and the products[3].
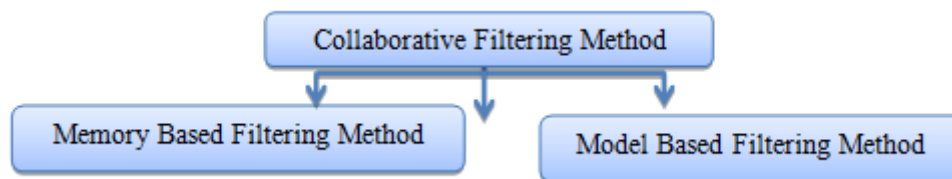

Fig. 1.1: Types of Collaborative filtering approach

Memory based: It uses the complete user item data to generate the prediction. It mainly uses statistical methods for filtering.
Model based**:** In the method firstly defined the user model by using the clustering, association, Bayesian and neural network. These methods are used to predict user's rating of unrated products.
In the proposed work collaborative filtering method is used in which two factor are considered that are user and item. On the basis of this work, some existing approaches are also considered to go through to enhance the knowledge about the collaborative filtering and its scope.

2. Related work

A recommender system based on collaborative filtering using ontology and dimensionality reduction techniques are proposed and worked on the issue of sparsity and scalability. Singular value decomposition approach finds the similar items and users in each cluster. Ontology is also worked well with the context based recommender system [4, 5]. Collaborative filtering approach is some time faces the issue of cold start when the ratings of the product are not available or zero. When very few amounts of ratings are available for the new product and it is called as Incomplete Cold Start problem. This problem is resolved by using Time- Aware collaborative filtering with deep learning [6]. This

type of problem is also solved by using the optimization approaches and algorithms. K-mean clustering with Cuckoo search Optimization algorithm is used in movie recommendation system on Movielens dataset. This system classifies the users on the basis of similarity in choice. Recommendation of this system is based on the K-mean clustering and Cuckoo optimization algorithm [7].

As the technology changes day by day, a large number of techniques are employed in the field of recommendation system. In recent works deep learning has employed for effective recommendation. In this model the interaction between the user and item features is resorted to matrix factorization. Then this is applied to latent features of users and items. This approach is called as Neural Network-based Collaborative filtering [8]. A hybrid recommendation system by using ontology and neuro-fuzzy techniques is proposed movie recommendation to the users. Semantic approach is used to compute the similarity between the products and demographic similarity measure is applied between each pair of users. Fuzzy rules are applied to achieve the more accuracy in recommendation [9]. Accuracy of the system is also improved by using clustering and association rules mining on the implicit data. Clustering approach resolve the issue of sparsity in the huge amount of data. It also reduces the data size and dimensionality of the item space.Collaborative filtering gives more effective results when it is extended with other techniques even when sparsity is also present in the data[10].

Semantic-based friend recommendation system is proposed which suggest the friends on the basis of lifestyles. In this method similarity between the lifestyles are matched and then recommend the fiend on that similarity. Latent Dirichlet Allocation algorithm is used to extract the style of the users of Friend book. Similarity metrics are used to measure the similarity between the styles and impact. The proposed method is implemented on the android phones and performance is evaluated on small scale and large scale [11]. Rank Aggregation approach is used for the product recommendation. used the feedback of the users related to the product and score given by them to the related product. This feedback is used by the rank aggregation algorithm for the recommendation. The performance of this system is evaluated by using the parameter false negative rates, false positive rates and precision. The variation in result over the existing method shows the effectiveness of the proposed method [12].
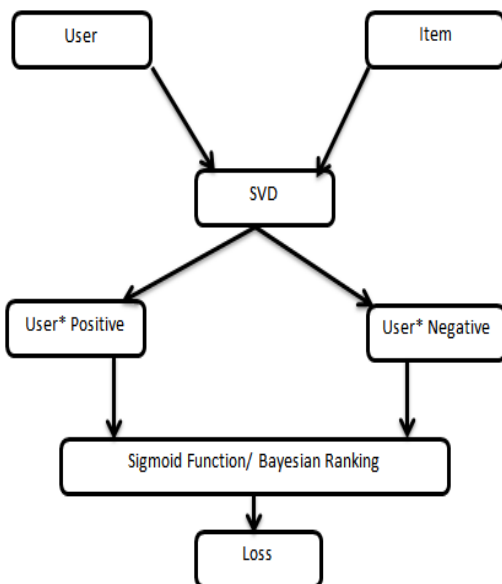
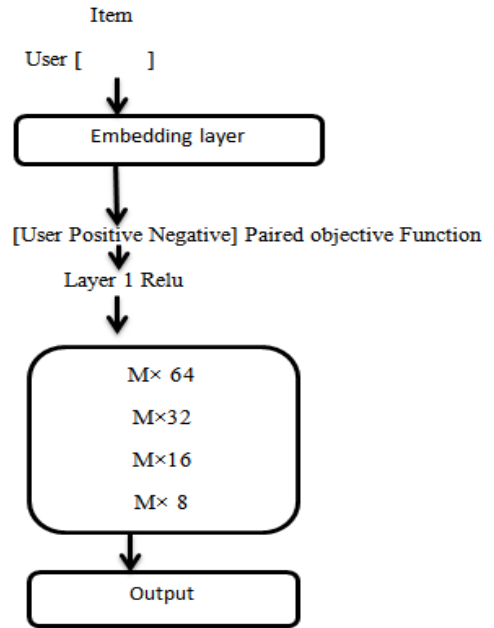## 3. Proposed Approach Architecture

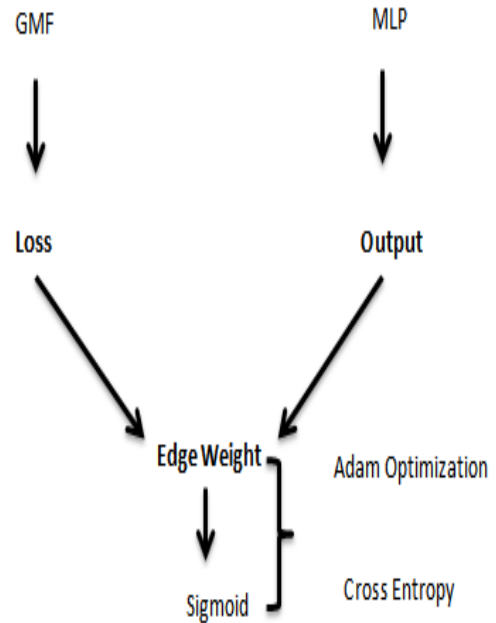**Fig. 3.1**

Fig. 3.2

Fig. 3.3

In the above given figure 3.1 it represents the initial part of the proposed approach in which latent features of the User and Movie review matrix is extracted. After this SVD is applied on this matrix for matrix factorization and then pair-wise objective function by using Bayesian ranking approach. In Pairwise objective function it uses user matrix and movie review matrix which use implicit review {1, 0}. This layer also calculate the los but it tune in the loss figure 3.1

In figure 3.2 it describes the MLP layer which extracts the threshold output by multilayer approaches. In this approach window size used is (64, 32, 16, and 8). These layers also reduce the non-linearity by using Relu layer. From figure 3.1 get loss and figure 3.2 get output tune and figure 3.3 architecture by using loss function which tune by Adam optimization. By these architecture the main objective is completed by reduction in loss and reduce the nonlinearity by pairwise objective function.

4. Proposed Algorithm

Step1   Fusion of Twomodels GMF (generalized matrix Factorization) and MLP (Multi-LayerPerceptron)
Sep2   Model based on implicit feedback
  a.   Input **User * items**
  b.   Latent vectors ←Apply SVD on the rating matrix R
  c.   GMF = $User_{4*2}$ * $Item_{5*2}$(*Dot Product of the latent vectors*)
  d.   *MLP*
i.   *Assume X number of hidden layers.*
ii.   Layer 1,
  1.   first, concatenate *vertically* the p_i and q_j latent vectors,
  a.   z1 = [pi,qj]...................   ....(4.1)

  b.   Output of layer 1 (*to be fed into layer 2*) => a1 * (W1 * z1 + b1)....   .. (4.2)
  2.   a1 = activation function (sigmoid.)
  W1 = Weights for instances, b1 = biasLayer X = The last layer..............   .... (4.3)

  3.   Output of the last layer = a_n * (w_n * z_n + b_n)...   .. (4.4)

  4.   Concatenate outputs of GMF and MLP (*vertical concatenation*),
  OP = [[$User_{4*2}$ * $Item_{5*2}$],

           [a_n * (w_n * z_n + b_n)]   ]...........   .... (4.5)

Yij' = σ * (h * OP)...............   **... (4.6)**

  a.   where, σ = activation function,
  b.   *h* = edge weights of the *O/P* layer

  e.   Minimize the "*loss*" function to tune the parameters

i.   ½ $\sum(Y_{ij}$' - $Y_{ij})^2$ + (λ / 2) ($(mod(U))^2$ + $(mod(V))^2$) .... (4.7)
ii.
iii.   Put the value of Y_{ij}' from equation (..1) above.

5. Proposed Approach Description

Implicit Data

Let M and N denote the number of users and items respectively so, matrix form
$$Z \in R^{M \times N}$$
$$R \leftarrow Vector\ Space$$
$$Z_{u,1} = \begin{cases} 1, & if\ user\ U\ given\ review\ for\ i \\ 0, & otherwise \end{cases} \quad ....$$ ..... (5.1)

Matrix Factorization (SVD)

In SVD Matrix factorize in three matrixes.
In proposed approach

$$A = User_{m \times n} * Item_{n \times m} ....$$ .... (5.2)

$$A = U\ S\ V^T ....$$ .... (5.3)

U ← User Matrix
$V^T \leftarrow Item\ Matrix$
$S \leftarrow Ranking\ Item$
Apply MLP (Multi-Layer Perceptron)

$$Z_1 = [P_i Z_i]...$$ .... (5.4)
Latent Vector of Users and items

Output Layer

$$O_1 = a_1 * (W_1 * Z_1 + b_1) ....$$ .... (5.5)

$$O_2 = a_2 * (W_2 * Z_2 + b_2) ....$$ .... (5.6)

$$O_n = a_n * (W_n * Z_n + b_n) \quad \text{...} \tag{5.7}$$

$O_n \leftarrow last\ output\ of\ MLP\ Layer$

In MLP Use Q₁ (Sigmoid Function)

$$f(x) = \frac{1}{1+C^{-x}} \text{...} \tag{5.8}$$

Objective Function

In proposed approach pair wise objective function is used.

$$\theta^{t+1} = \theta^t + \eta * \frac{\partial 0(\theta)}{\partial \theta} \text{...} \tag{5.9}$$

$\theta^{t+1} \leftarrow ranking\ of\ item\ at\ (t+1)\ time$
$\theta^t \leftarrow ranking\ of\ item\ at\ t\ time$
$\eta \leftarrow Learning\ rate$
$\frac{\partial 0(\theta)}{\partial \theta} \leftarrow Minimizing\ Error$

In pairwise objective function apply on the both latent and feature vector of user and item.

Concatenate GMF and MLP

In proposed use vertical concatenation of latent feature come from GMF and output come from MLP so,

$$OP = \left[[User * Item] a_n (W_n * Z_n + b_n) \right] \text{.................................} \tag{5.10}$$

$$Y'_{i,j} = \sigma * (h * \partial P) \text{.....................................} \tag{5.11}$$

$\sigma = activation\ Function$
$h = edge\ weight\ od\ output\ layer$

Loss Function

Tune the equation by loss function

$$Loss\ function = \frac{1}{2} \sum (Y'_{ij} - Y_{ij})^2 + \frac{1}{2} ((mod\ (v)^2) + (mod(v)^2)) \text{.....} \tag{5.12}$$

$Y'_{ij}\ from\ equation\ (5.11)$

6. Results and Discussion

6.1 Experimental Settings

Movie Lens: For collaborative filtering approach for movie rating dataset Movie lens is widely used. In the proposed work 1 Million ratings data set is used in which each user has at least 20 ratings. In this work implicit feedback is used for investigate the performance of the learning. On implicit data each entry is marked as 0 and 1 whether the user has rated the item.In this section, we compare the proposed NMF with DMF. As our proposed methods aim to model the relationship between users and items, we mainly compare with user-item models.

Table 6.1: DMF (Deep Matrix Factorization)

Dataset	NDCG	H.R
Movie lens 100K	0.389	0.652
Movie Lens 1M	0.381	0.623

Observation 1: In the above given table 6.1 Comparison of DMF approach on the movie lens dataset with 100 K and 1Million instance is done. In analysis use NDCG which show that how much generalize matrix.In case of 100K 38.9% and 1M show 38.1% .In case of hit ratio (HR) it also decreases which is indirectly represent accuracy.
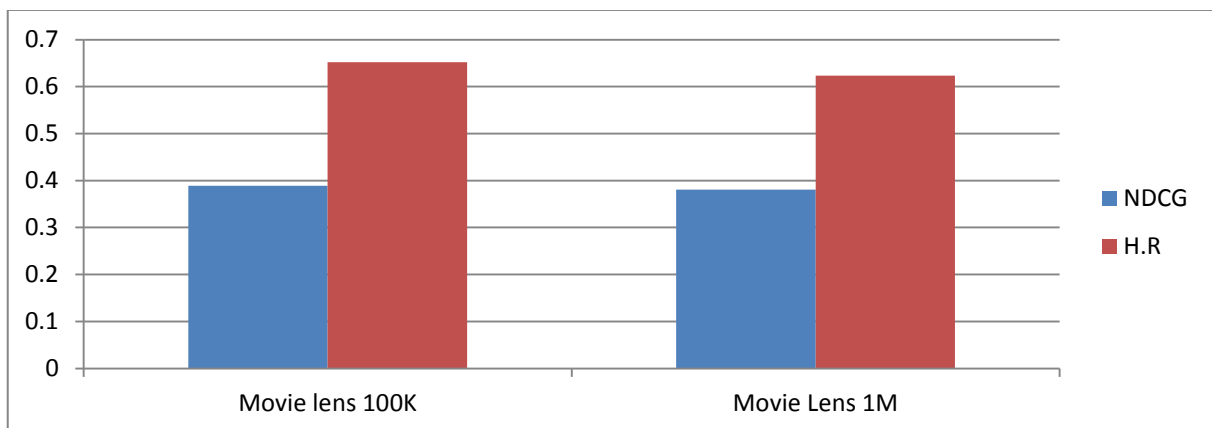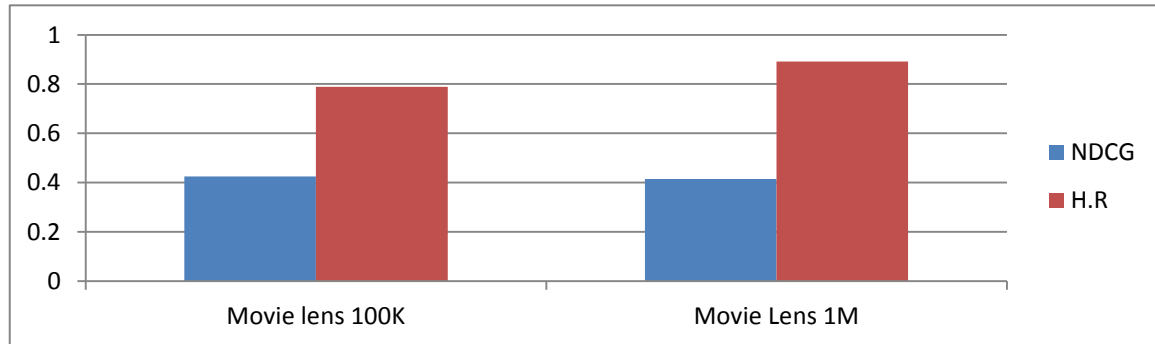

Fig. 6.1: Comparison between 1K and 1M dataset with DMF

Table 6.2: Proposed Approach Results

Dataset	NDCG	H.R
Movie lens 100K	0.425	0.789
Movie Lens 1M	0.415	0.892

Observation2: In table 6.2the Comparison of proposed approach on the movie lens dataset with 100 K and 1Million instance is presented in the graphical form. In analysis NDCGis used which show that how much matrix is generalize. In case of 100K 42.5% and 1M it is 41.5% .In case of hit ratio (HR) it increase and show opposite behavior to DMF which indirectly represent the accuracy. The reason behind its improvement is pairwise objective function which generalize user and movie review at same time.

Fig. 6.2: Comparison between 1K and 1M dataset with Proposed
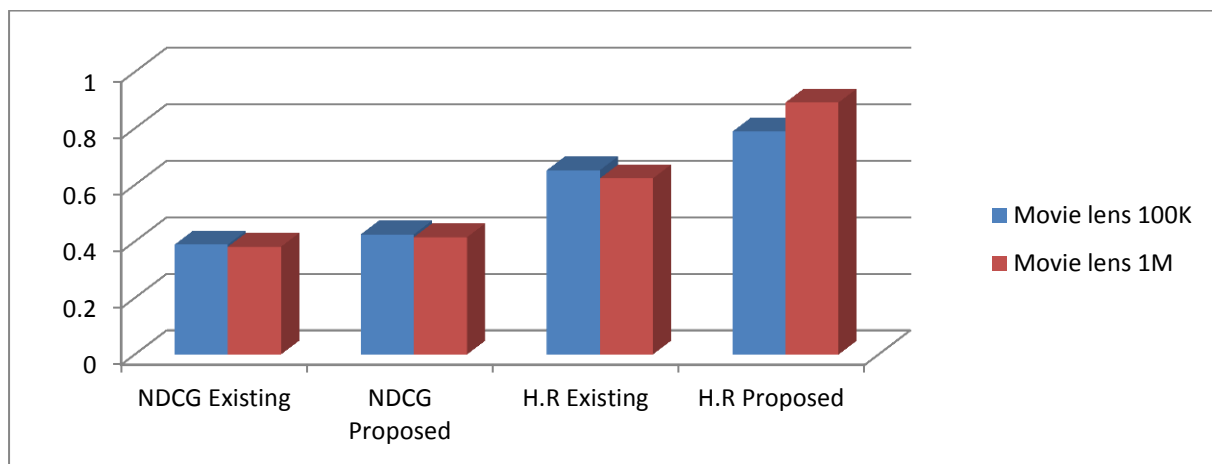
Fig. 6.3: Comparison of Proposed and Existing approach result

7. Conclusion

The proposed work explores the neural network architecture for collaborative filtering. The implicit movie reviews are generalized by NCF using Gaussian ranking and tune by loss function which is given in equation 5.11. The observations in the results clearly show the significant improvement in H.R. In this work pair wise objective function is used for emphasis of non-linearity and latent features and the proposed approach is combination of pairwise objective function with point wise objective and tune by cross entropy with Adam optimization which optimize version of gradient descent. In empirical analysis use 1K and 1M movie lens dataset and compare with deep matrix factorization (DMF)

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