Incremental Associative Memory Model Algorithm for Highly Scalable Recommender Systems

Neha Agarwal
Dayalbagh Educational Institute
Agra, India

Prashant
Madhav Institute of Technology & Science
Gwalior, India

ABSTRACT
Recommender systems are smart and intelligent systems that often seem to know users more than users know themselves. Recommender system helps customers by recommending products they will probably like or purchase based on their purchasing, searching, browsing history and also the other similar customer's history. Their aim is to provide efficient personalized solution in E-commerce domain that would benefit both buyer and seller. In this paper, authors proposed a neural network based approach called Associative Memory Model (AMM) to recommend items to users and also explain Incremental AMM for dynamic dataset. Experiments are carried out to observe the performance of the proposed algorithm and compare results with the existing traditional collaborative filtering algorithm .The property of AMM is that they are able to solve the pattern completion problem. This property can be used to build an efficient recommender system for E-commerce website that can produce more accurate and quick results than the others.

Keywords
Recommender systems, Collaborative filtering, neural network, Associative memory model

1. INTRODUCTION
Recommender system is a technique that is used by E-commerce website to suggest new items for a user, based on the user's previous behavior and other similar user's behavior. By now, on line shopping store, like Netflix.com suggest which video to watch, Pandora and last .fm suggest which music we will like to listen, Amazon.com and Flipkart.com suggest which products (like books, mobile phone, laptop etc) should us buy.

One of the most successful technologies among recommender system is Collaborative Filtering (CF) [1]. Numerous commercial on line companies apply this technology to provide recommendation to their customer to boost their sale. The fundamental challenge for existing CF systems is to improve the quality of recommendations for the users. Recommender systems should be such that user can trust on them. Among the millions of items if recommendation system suggest items for users which is actually needed by users then user will rely on these system and in future he would like to use them again. On the other hand if recommender systems generate false recommendation, user purchase that item and find out that the item is no use of him, user would not like to use these systems again in future.

There are two types of error commonly occur in recommender systems first is false positive and the other one is false negative [2] [3].False positive implies that recommender system is recommended those items for users which are not like by them and false negative implies that recommender system is not recommended those items for users which actually will be like by them. In E-commerce domain, false positive is more dangerous than false negative since these errors will lead to refusing the use of recommender system in future. To overcome these problems, New recommendation system approaches are needed that can produce high quality of recommendations.

In this paper, authors present an approach to address these issue by using a new CF model, constructed based on the neural network based approach called Associative Memory Model (AMM). It is chosen because associative memory maps a set of input pattern to a set of output pattern. This is a type of memory that recall the data based on the degree of similarity between the input pattern and pattern stored in the memory. The paper is organized as follows: section 2 outlines related work; section 3 describes how the AMM algorithm is employed in our proposed recommender system. Section 4 describes incremental AMM algorithm. Section 5 then briefly reports on some common evaluation metrics. Section 6 provides experimental results and analysis. Finally section 7 concludes the paper.

2. LITERATURE REVIEW
In 1992, Goldberg implements Tapestry, one of the earliest implementations of collaborative filtering-based recommender systems [4]. This system relied on the explicit opinions of people from an office workgroup. In 1994, Resnick proposed a recommender system based on collaborative filtering for recommend news to newsgroup's users using Pearson correlation coefficient (computing the similarity between two users in this article) [5]. In 1998, Breese described CF techniques based on correlation coefficient, vector similarity, and statistical Bayesian methods and compared the predictive accuracy of the various methods in a set of representative problem domains [6].

Although collaborative filtering methods has been successfully deployed in various fields [Grouplens News, MovieLens, Ringo, Amazon] it suffers from two serious problems: the data sparsity problem and the scalability problem. The data sparsity in high dimensional data makes it very difficult to find other users which are similar to the target users. As recommender system has to give real time recommendations, so scalability is another issue in the high dimensional data as, high dimensional data require a lot of computation. For solving these problems, a lot of study has been made until 2000. In 2000 Goldberg [7] proposed a CF algorithm called eigentaste that applies PCA to the resulting dense subset of rating matrix for reducing the dimensionality. In 2001, Sarwar [8] proposed item based collaborating filtering algorithm to address the sparsity and scalability. In 2003, Linden [9] applied this algorithm to commercial recommender system such as Amazon.com.

In 2003, Li and Kim applied clustering technique to the item based collaborative filtering to solve the coldstart problem [10]. In 2004, Cheung used the latent class model (LCM) to alleviate the sparsity problem. They proposed the use of a pair of LCMs (called dual latent class model – DLCM), instead of a single LCM, to model customers' likes and dislikes separately for enhancing the prediction accuracy [11]. In 2007, Li described a collaborative music recommender system(CMRS) based on their proposed item-based probabilistic model, where items are classified into groups and predictions are made for users considering the Gaussian distribution of user ratings to alleviated problem of data sparsity, coldstart and quality of recommendation [12]. In 2008, Ahn proposed new heuristic similarity measure to improve the quality of recommendation [13].

Neural networks are also able to built efficient recommender systems [14]. In 2006, Meehee Lee proposed a new collaborative filtering algorithm using Self Organizing Map (SOM) for improving the scalability and the performance of the traditional collaborative filtering technique [15]. In 2009, SongJie Gong proposed an item based collaborative filtering using Back-Propagation neural networks for improving the quality of recommendation [16].

Authors work explores the extent to which AMM, a new algorithm of CF based recommender system is able to improve the quality of recommendation and also describe incremental AMM for dynamic dataset.

3. ASSOCIATIVE MEMORY MODEL ALGORITHM

In AMM based collaborative filtering algorithm, there are m users $\{u_1, u_2, \ldots\ldots u_m\}$ and, n items $\{i_1, i_2, \ldots\ldots i_n\}$. In this first we encodes associations $\{A_i, A_i\}$ for each user pattern vector (where $A_i \in \Re^n$ and A_i is the user pattern vector of u_i). Then compute correlation matrix W, by adding all these association of m users. Once the correlation matrix is computed item is recommended to target user by applying decoding (map input vector of target user to the output vector on the degree of similarity between the target user pattern and other users pattern stored in the memory) For decoding feed forward linear network consist input and output layer of n neurons is used. Weights are computed during encoding process.

3.1 Correlation Matrix Computation

Our first step in the AMM based collaborative filtering algorithm is to compute correlation matrix for computing similarity between items. The process of constructing the correlation matrix is called encoding. During encoding the weight values of correlation matrix $w(i)$ for an association pattern pair $\{A_i, A_i\}$ is computed as [17]:

$$w(i) = (A_i - \bar{a}_i)^T * (A_i - \bar{a}_i) \quad (1)$$

Where $\bar{a}_i$ is the mean value of pattern A_i. Then connection matrix W_m is the summation of weights of m users given by [17]:

$$W_m = \alpha * \sum_{i=1}^{m} w(i) \quad (2)$$

Where α is the normalizing constant equals to 1/m and $W_m \in \Re^{n*n}$.

3.2 Prediction Computation

Once connection matrix is computed next step is to generate prediction for target user by applying decoding or mapping. Given an input vector of target user X, prediction of item i for target user X is computed as y_i output of neuron i due to the combined action of the component of the key pattern X is given by [17]:

$$y_i = \bar{x} + c * \sum_{i=1}^{n} x_j * w_{ji} \quad (3)$$

Or

$$Y = \bar{x} + c * X * W_m \quad (4)$$

Where the mean rating given by target user X and c is the constant use for normalizing equal to 5/m (experimentally determined). $Y \in \Re^n$ is the output vector for target user in terms of prediction of list of items.

4. INCREMENTAL ASSOCIATIVE MEMORY MODEL ALGORITHM

AMM has a property that allows the model to be incrementally computed. This method is used to handle dynamic databases, where new users and items may arrive once the model is built. First compute a suitably sized model and then use the projection method to build incrementally upon that as shown in Figure 1.

When new user arrives we encode associations for new user and add it with previously computed correlation matrix of m users.

$$W_{m+1} = W_m + (A_u - \bar{a}_u)^T * (A_u - \bar{a}_u) \quad (5)$$

Where A_u is the association vector of new user u and $\bar{a}_u$ is the mean value of pattern A_u. W_{m+1} is the incremented correlation matrix.

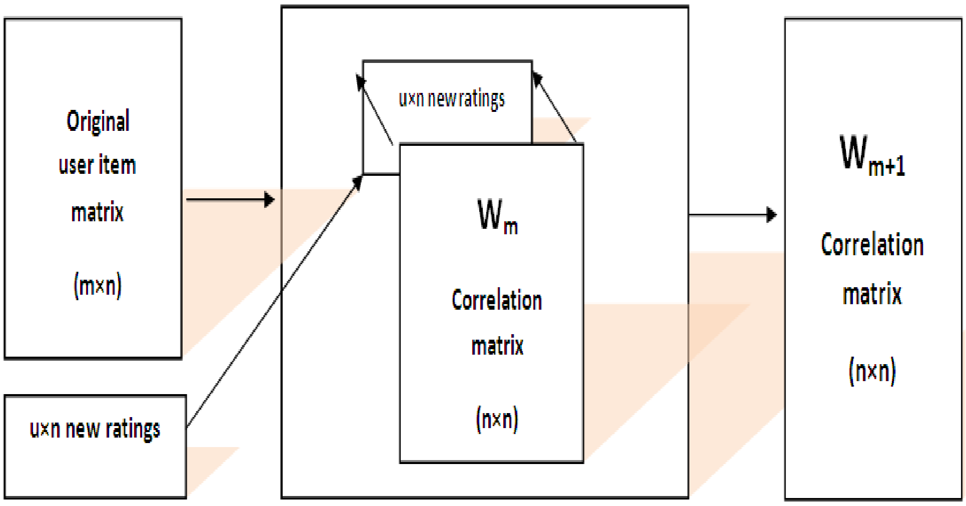

Fig 1: Schematic diagram of the Incremental AMM technique

5. EXPERIMENTAL EVALUATION

5.1 Dataset

In order to illustrate the performance of proposed method, MovieLens dataset (http:/www.movielens.umn.edu) publically available at GroupLens website is used. The MovieLens dataset consist of 100,000 ratings (consider only those users who has rated 20 or more than 20 movies) which were given by 943 users on 1682 movies. For experiment, from the initial dataset, five data were generated. Each data consist of 80% of original dataset for training (u1.base, u2.base, u3.base, u4.base, u5.base) and 20% of dataset for testing (u1.test, u2.test, u3.test, u4.test, u5.test).

5.2 Experimental Setup

All experiments were implemented using MATLAB 7.5 and conducted on a PC with Intel Pentium M processor with 1.70GHz with 1GB Ram.

5.3 Evaluation Metric

Most popular metric Mean Absolute Error (MAE) is used to evaluate the effectiveness of proposal work. It measures the average absolute deviation between a predicted rating and the true rating [17].

$$MAE = \frac{\sum_{\{u,i\}} \left| p_{u,i} - r_{u,i} \right|}{N} \qquad (6)$$

Where $p_{u,i}$ is the predicted rating for user u on item i ,$r_{u,i}$ is the actual rating and N is the total number of rating in test dataset.

6. EXPERIMENTAL RESULTS

6.1 Prediction Quality Experiments

Authors evaluated AMM approach based on the metric MAE. Mean absolute error for AMM based

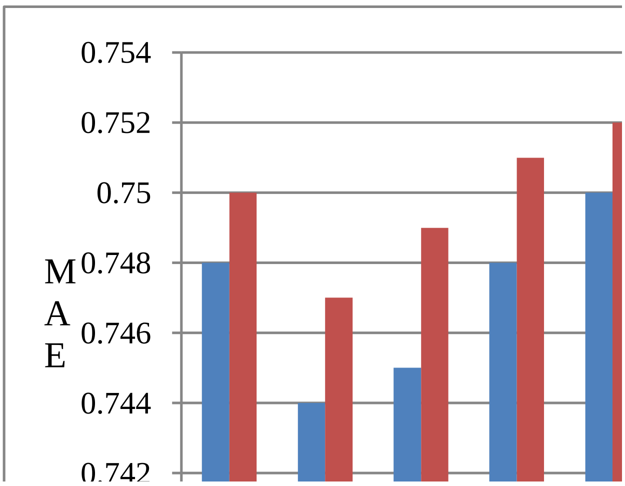

Fig 2: Comparison of prediction quality of AMM based collaborative filtering (proposed) and traditional collaborative filtering algorithms (existing)

Table1. Training and Prediction Time for each split of AMM based collaborative filtering

Split	Training Time(sec)	Prediction Time(sec)
Split-1	6.85	2.134
Split-2	9.54	4.677
Split-3	18.45	3.55
Split-4	19.72	4.10
Split-5	19.73	4.23

collaborative filtering and traditional collaborative filtering [17] is calculated for each data group called split and the results are shown in Fig 2. Average MAE of AMM based method is 0. 747 and average MAE of traditional collaborative filtering is 0.749. Result shows that AMM based collaborative filtering method is better than traditional collaborative filtering.

6.2 Performance Implication

Proposed algorithm generates 20,000 ratings in 19.5866 second (training and prediction time combine) from those a throughput rate of 1021.106 recommendations per second (average) is obtained as shown in Table 1.

7. CONCLUSION

In this paper, authors explain and experimentally evaluated a new algorithm for CF-Based recommender systems. Results show that AMM technique is useful for large scale dataset and also produce accurate and quick results than other techniques. Proposed algorithm is also easily scalable for dynamic dataset.

MovieLens dataset have an important constraint that every user has at least 20 rating, which is enough number of rating for finding the neighbors .*Cold start* is one the issue that authors plan to consider for addressing this problem in the future.

8. ACKNOWLEDGMENTS

Authors would like to thank the GroupLens members from University Of Minnesota for making the MovieLens dataset publically available for researchers.

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