CHAPTER 6

KNOWLEDGE BASED FUZZY-NEURO COLLABORATIVE FILTERING MODEL (KBFNM)

6.1 INTRODUCTION

Due to the growth in amount of information on the web and increase in number of web users, there is a need for web based applications which provides support for searching the information to the web users. The user’s online behaviour in recommender systems are also uncertainty in defining preferences and profile. Crisp rule based recommender systems have their characteristic feature of sharp cut-offs for continuous attributes. Instead it is discretize the continuous values into low, medium and high. Fuzzy logic recommender system typically provides solutions to assist users in converting attribute values to fuzzy values for handling uncertainty due to subjectivity, imprecision and vagueness in profile and preferences.

This chapter introduces novel Knowledge Based Fuzzy-Neuro CF Model (KBFNM) for recommender system which combines the best practices of fuzzy logic and neural network in order to extract business intelligence from real-world datasets. KBFNM model uses Fuzzy Logic (FL) to meet the uncertainty of user on-line behaviour and neural networks to handle huge mass of data, improving the accuracy and relevancy of predictions. This intelligence is ultimately used to business by generating recommendations and users to reduce the search time and select the right products on web. This KBFNM model is implemented and experimentally evaluated with different parameters using real world datasets.
6.2 RELATED WORKS

In this section the related works of fuzzy logic and artificial neural network based recommender systems have been discussed.

G. Castellano et al. [28] presented a neuro-fuzzy strategy that combines soft computing techniques to develop web recommendation system that dynamically suggest interesting URLs for the current user. User access logs are analysed to identify user sessions as a preliminary step. The groups of user’s common browser behaviour are discovered by applying a fuzzy clustering algorithm to the user sessions. Finally, a knowledge extraction process is carried out to derive associations between user profiles and relevant web pages to be suggested to users. In order to derive knowledge from session data and represent it in the comprehensible form of fuzzy rules a hybrid approach based on the combination of the fuzzy reasoning and connection paradigm has been proposed by this author.

G. Castellano et al. [29] proposed the use of a neuro-fuzzy strategy to develop a Web personalization framework for the dynamic suggestion of URLs retained interesting for the currently connected users. In particular, a hybrid strategy exploiting the combination of the fuzzy logic with the neural paradigm is proposed in order to discover useful knowledge from session data identified from the analysis of log files and represent it in a set of fuzzy rules expressed in an interpretable form.
De Campos et al. [18] proposed a model by combining Bayesian network for governing the relationships between the users and fuzzy set theory for presenting the vagueness in the description of user’s ratings.

Soheila Ashkezari-T et al. [76] contribution using genre based information in a hybrid fuzzy-Bayesian network collaborative RS is suggested. The interest to the different genres is computed based on a hybrid user model. They calculated similarity of likeminded users according to the fuzzy distance and also Pearson correlation coefficient is involved in a Bayesian network. The author call the RS uses as Bayesian network RS (BNRS), use Pearson for similarity computations named it PBNRS and using fuzzy distance for similarity computation called it FBNRS.

Maral Kolahkaj et al. [56] presented the fuzzy-neural network for finding users movement pattern using fuzzy clustering technique and web usage mining. The author has presented a method to deal with limitations of conventional methods. Their system finds useful movement pattern of users and also presents user's future requests by using fuzz-neural network.
6.3 KNOWLEDGE BASED FUZZY-NEURO CF MODEL (KBFNM)

In this Section, Knowledge Based Fuzzy-Neuro Model for collaborative recommender system for providing high potential recommendations has been discussed. The Figure 6.1 shows the proposed knowledge based fuzzy-neuro CF model architecture.
6.3.1 Methodology

KBFNM is divided into three sub phases. The First phase is pre-processing works in offline. In this phase data is pre-processed using various pre-processing techniques such as feature selection, normalization and data reduction. In the Second phase modeling is constructed in offline. Active user’s knowledge about the data such as profile and preferences are defined and applied in terms of crisp rules and/or fuzzy rules on utility matrix. SOM Clustering is applied to identify the user navigation patterns or to cluster similar users. Once the user navigation patterns are identified using clustering the active user’s best matching cluster is predicted using BPN classification to generate recommendations. Final phase is obtaining business intelligence i.e. recommendation generation process for the active user is performed online process.

6.3.1.1 Pre-Processing

The essential pre-processing steps discussed in the earlier chapters such as feature selection and dimensionality reduction techniques have been applied to select relevant features and samples.

The feature selection algorithms are designed with different strategies broadly fall into three categories: Filter, wrapper and embedded models. The Filter model relies on the general characteristics of data and evaluates features without involving any learning algorithm. The wrapper model requires a predetermined learning algorithm and uses its performance as evaluation criterion to select features. Algorithms with embedded model
incorporate variable selection as a part of the training process, and feature relevance is obtained analytically from the objective of the learning model.

Missing values are replaced with values using neural networks. The back propagation feed forward neural network is used to replace the missing values. The user-item rating matrix is normalized between 0 and 1. The Principal Component Analysis technique is used to reduce the dataset from high to low.

6.3.1.2 Model Construction

In this second phase, knowledge based fuzzy-neuro CF recommender system model is constructed using Fuzzy Logic and Artificial Neural Networks. This phase has three steps, knowledge base step is used to filter of users and/or items using rules, clustering of user-item rating matrix using SOM and predicting BMC of active user using Back Propagation Neural Network (BPN) classification

Knowledge Base

In the first step, the active user’s knowledge information such as profile and preferences are presented in the form of if-then rules and applied. Users or items in the dataset are filtered based on knowledge defined in terms of these crisp/fuzzy rules to identify the user’s navigation pattern.

When there is uncertainty in user’s preferences and profiles, fuzzy rules are defined on membership function. The profile and preferences are also considered as fuzzy
variables. When the active user is new to recommender system (Cold-start problem) the proposed model generates recommendation based on knowledge filtering of users based on demographic information and preferences of active user. The users or items satisfying the crisp/fuzzy rules are filtered to reduce the dataset for mining business intelligence.

**Clustering of Utility Matrix using SOM**

In this second step, the user-item rating matrix is clustered to identify the group of similar users. Since the dataset contains multidimensional data with more number of features and user, neural network based SOM clustering is used to group the users to find the users navigation patterns.

**Identifying BMC using BPN**

Finally, active user’s best matching cluster (BMC) is identified using back propagation neural network classification technique. Resilient back propagation neural network is used to identify matching cluster of active users. The steps are involved in RBPN classification is discussed in Chapter 4.

**6.3.1.3 Recommendation**

Once the Best Matching Cluster (BMC) is identified using back propagation neural network, this model generates the list of top-N recommended items based on the BMC of user’s navigation pattern of sorted frequency count items. The list
of recommendations for the active user is generated by finding the list of items from the selected cluster which are not purchased by the active user.

6.3.2 KBFNM Algorithm

The Knowledge Based Fuzzy-Neuro Collaborative Filtering (KBFNM) Model algorithm is presented in this section. This algorithm shows the pseudo code of the KBFNM model. The time complexity of this algorithm is $O(n+K)+O(W^3)+ O(m^2+m)$ where $K$ is total number of neurons. The space complexity of the algorithm is $O(1)$.

**Input:** Training Dataset $D$ and Test dataset $TD$.

The number of clusters $k$.

$N = \text{Potential number of recommendation}$.

**Output:** Recommendation List $\{I_1, I_2, ..., I_n\}$ of Top-$N$ items.

```
// Phase I: Pre-processing

Select relevant features using Feature Selection.

Replace missing values using NN.(if any)

Perform Normalization.

Do Dimension Reduction using PCA.

// Phase II: Model Construction

Define KB crisp rules (if any) for user preferences and/or profiles.

//Formulate the fuzzy rules (FR).

- Define the linguistic variables and terms (initialization).
- Construct the membership functions (initialization).
- Construct the rule base (initialization).

Convert crisp input data to fuzzy values using membership functions.
```
// Fuzzification of attributes/user preferences.

\[ \text{compute } \mu_s(a_j) \text{ where } j = 1 \text{ to } m. \]

// Fuzzification of samples/user profile features.

\[ \text{compute } \mu_s(p_j) \text{ where } j = 1 \text{ to } m. \]

Define KB fuzzy rules for user preferences and/or profiles

Apply rules and generate the resultant dataset.

**If** New User // **Cold-Start Problem**

Register and Login.

Go to Step 2 of Phase III.

**Else**

Clustering of utility matrix using SOM

//Predicting Best Matching Cluster (BMC) of active user.

**For** each Active user in TD do

Find the Best Matching Cluster (BMC) using RBPN.

**End**

TMAE ← Evaluate Matching Cluster

**End If**

//**Phase III: Recommendation**

**For** each Active user in TD do

Identify items from Best Matching Cluster (BMC) of users.

Calculate the frequency count and rank the items.

Select and recommend top-\(N\) items.

**End**

**Algorithm KBFNM**
6.4 EXPERIMENTAL RESULTS

This section presents detailed experimental results of KBFNM model. First the quality of clustering is analysed and validated using Silhouette Index. Second, the results of prediction evaluation using TMAE are presented. Third, recommendation quality evaluation with different parameters is presented. KBFNM model has been experimentally simulated and evaluated with two real-world datasets namely MovieLens 100k data set and Jester dataset with different active users profile and preferences.

6.4.1 Clustering Quality Analysis

The influence of various numbers of clusters k=2 to N/2 on clustering quality is examined. The optimum numbers of are usually tested between 2 and N/2. The Table 6.1 shows Mean Silhouette Index value for k=2 to N/2 number of clusters calculated using SOM and Fuzzy C Means (FCM) Clustering algorithm.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>SOM Clustering</th>
<th>FCM Clustering</th>
</tr>
</thead>
<tbody>
<tr>
<td>MovieLens</td>
<td>0.40</td>
<td>0.30</td>
</tr>
<tr>
<td>Jester</td>
<td>0.45</td>
<td>0.39</td>
</tr>
</tbody>
</table>

The experimented result shows that there is a significant difference in SOM clustering and FCM clustering. The mean Silhouette Index of Neural Network based SOM Clustering is 10% better quality partition based FCM clustering using MovieLens dataset. The Mean Silhouette Index of neural network based SOM clustering is 6% better
quality partition based FCM clustering using Jester dataset. Hence, the SOM clustering is capable of handling large volume of dataset with better accuracy.

Figure 6.2 shows the number of samples assigned to each neurone in the SOM Hit plot experimented for $k = 16$. It demonstrates the SOM Layer, with each neuron showing the number of samples assigned that it classifies. The relative number of samples for each neuron is shown via the size of the coloured patch.

*Fig 6.2 Sample SOM Hit Plot for $k=16$.***
6.4.2 Prediction Accuracy Analysis

The TMAE between the predicted ratings and the actual ratings of users within the test set can be calculated by averaging the Mean Absolute Errors of all active users. Table 6.2 shows prediction accuracy of various proximity metrics experimented using KBFNM model.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>RBPN</th>
<th>Euclidean</th>
<th>Correlation</th>
<th>Cosine</th>
</tr>
</thead>
<tbody>
<tr>
<td>MovieLens</td>
<td>0.105</td>
<td>0.1412</td>
<td>0.1795</td>
<td>0.1801</td>
</tr>
<tr>
<td>Jester</td>
<td>0.101</td>
<td>0.1132</td>
<td>0.1217</td>
<td>0.1264</td>
</tr>
</tbody>
</table>

Figure 6.3 shows prediction accuracy of various proximity metrics experimented using KBFNM model. The x-axis shows the proximity measures and y-axis shows the TMAE.

![TMAE Graph](image)

**Fig 6.3 Prediction Accuracy TMAE.**

The above pictorial representation shows that the TMAE of BPN classification is less than the other proximity measures using MovieLens and Jester datasets. Due to the fuzzy behaviour, the number of test active users in Jester dataset is less than that of MovieLens dataset the accuracy is increased.
6.4.3 Recommendation Quality Analysis

The KBFNM model is tested by taking range of recommendations using MovieLens dataset from 10 to 50 in the step of 5 and 5 to 30 in the step of 5 using Jester dataset for top-N=10.

**Recommendation Quality Evaluation using MovieLens dataset**

The Table 6.3 shows the Mean Recall, Precision and F1 Measures of KBFNM model using MovieLens dataset.

<table>
<thead>
<tr>
<th>Top-N</th>
<th>Recall</th>
<th>Precision</th>
<th>F1</th>
<th>Recall</th>
<th>Precision</th>
<th>F1</th>
<th>Recall</th>
<th>Precision</th>
<th>F1</th>
<th>Recall</th>
<th>Precision</th>
<th>F1</th>
<th>Recall</th>
<th>Precision</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0.7094</td>
<td>0.8500</td>
<td>0.7217</td>
<td>0.7421</td>
<td>0.7812</td>
<td>0.7541</td>
<td>0.8956</td>
<td>0.6083</td>
<td>0.7143</td>
<td>0.8671</td>
<td>0.5784</td>
<td>0.6652</td>
<td>0.8015</td>
<td>0.6519</td>
<td>0.6645</td>
</tr>
<tr>
<td>15</td>
<td>0.8330</td>
<td>0.7100</td>
<td>0.6481</td>
<td>0.9072</td>
<td>0.6265</td>
<td>0.6456</td>
<td>0.9485</td>
<td>0.5001</td>
<td>0.5722</td>
<td>0.9549</td>
<td>0.4825</td>
<td>0.5790</td>
<td>0.9364</td>
<td>0.5272</td>
<td>0.5683</td>
</tr>
<tr>
<td>20</td>
<td>0.8978</td>
<td>0.6215</td>
<td>0.6431</td>
<td>0.9454</td>
<td>0.5381</td>
<td>0.6123</td>
<td>0.9507</td>
<td>0.4186</td>
<td>0.5155</td>
<td>0.9635</td>
<td>0.4037</td>
<td>0.5229</td>
<td>0.9662</td>
<td>0.4454</td>
<td>0.5128</td>
</tr>
<tr>
<td>25</td>
<td>0.9325</td>
<td>0.5508</td>
<td>0.6207</td>
<td>0.9632</td>
<td>0.4571</td>
<td>0.5615</td>
<td>0.9673</td>
<td>0.3577</td>
<td>0.4655</td>
<td>0.9635</td>
<td>0.3455</td>
<td>0.4745</td>
<td>0.9733</td>
<td>0.3863</td>
<td>0.4663</td>
</tr>
<tr>
<td>30</td>
<td>0.9616</td>
<td>0.5077</td>
<td>0.5728</td>
<td>0.9791</td>
<td>0.4099</td>
<td>0.5253</td>
<td>0.9644</td>
<td>0.3093</td>
<td>0.4210</td>
<td>0.9832</td>
<td>0.2825</td>
<td>0.4353</td>
<td>0.9752</td>
<td>0.3328</td>
<td>0.4288</td>
</tr>
<tr>
<td>35</td>
<td>0.9717</td>
<td>0.4620</td>
<td>0.5541</td>
<td>0.9816</td>
<td>0.3614</td>
<td>0.4911</td>
<td>0.9796</td>
<td>0.2717</td>
<td>0.3836</td>
<td>0.9773</td>
<td>0.2396</td>
<td>0.4062</td>
<td>0.9858</td>
<td>0.2997</td>
<td>0.3685</td>
</tr>
<tr>
<td>40</td>
<td>0.9834</td>
<td>0.4220</td>
<td>0.5265</td>
<td>0.9816</td>
<td>0.3302</td>
<td>0.4450</td>
<td>0.9810</td>
<td>0.2217</td>
<td>0.3238</td>
<td>0.9773</td>
<td>0.2017</td>
<td>0.3751</td>
<td>0.9897</td>
<td>0.2508</td>
<td>0.3504</td>
</tr>
<tr>
<td>45</td>
<td>0.9834</td>
<td>0.3851</td>
<td>0.4894</td>
<td>0.9816</td>
<td>0.2877</td>
<td>0.4109</td>
<td>0.9810</td>
<td>0.1974</td>
<td>0.2956</td>
<td>0.9773</td>
<td>0.1782</td>
<td>0.2909</td>
<td>0.9897</td>
<td>0.2371</td>
<td>0.3262</td>
</tr>
<tr>
<td>50</td>
<td>0.9834</td>
<td>0.3526</td>
<td>0.4679</td>
<td>0.9816</td>
<td>0.2616</td>
<td>0.3852</td>
<td>0.9810</td>
<td>0.1838</td>
<td>0.2772</td>
<td>0.9773</td>
<td>0.1591</td>
<td>0.2697</td>
<td>0.9897</td>
<td>0.2127</td>
<td>0.3094</td>
</tr>
</tbody>
</table>

From the table, it is observed that the maximum mean F1 measure of KBFNM model is 75 % and the corresponding recall and precision are 74% and 78% respectively.
Comparison of Recall

Figure 6.4 shows mean Recall measure of various number N of recommendations calculated using KBFNM model. The x-axis shows the number of recommendations N and y-axis shows the mean Recall value. This pictorial representation clearly shows that the maximum mean Recall value is obtained using MovieLens dataset-3 for number of recommendations.

![Fig 6.4 Mean Recall of top-N recommendations using MovieLens dataset.](image-url)
Comparison of Precision

Figure 6.5 shows mean precision measure of various number N of recommendations calculated using KBFNM model with MovieLens dataset. The x-axis shows the number of recommendations N and y-axis shows the mean precision measure. This pictorial representation clearly shows that the maximum mean precision value is obtained using MovieLens dataset-1 for number of recommendations.

![Fig 6.5 Mean Precision of top-N recommendations using MovieLens dataset.](image-url)
Comparison of F1 Measure

Figure 6.6 shows mean F1 measure of various number N of recommendations calculated by KBFNM model using MovieLens dataset. The x-axis shows the number of recommendations N and y-axis shows the mean F1Measure. This pictorial representation clearly shows that the maximum mean F1 Measure value is obtained using MovieLens dataset-2 for number of recommendations.

*Fig 6.6 Mean F1 of top-N recommendations using MovieLens dataset.*
Recommendation Quality Evaluation using Jester dataset

The experiment is repeated with range of N values from 5 to 30 in the step 5 and calculated the mean Recall, Precision and F1-Measure using Jester dataset. The Table 6.4 shows the mean Recall, Precision and F1 Measures of KBFNM model using Jester dataset.

**Table 6.4 Mean Recall, Precision and F1 of KBFNM using Jester dataset**

<table>
<thead>
<tr>
<th>TOP-N</th>
<th>Jester dataset - 1</th>
<th>Jester dataset – 2</th>
<th>Jester dataset - 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Recall</td>
<td>Precision</td>
<td>F1</td>
</tr>
<tr>
<td>5</td>
<td>0.3407</td>
<td>0.9700</td>
<td>0.5062</td>
</tr>
<tr>
<td>10</td>
<td>0.6915</td>
<td>0.9770</td>
<td>0.8267</td>
</tr>
<tr>
<td>15</td>
<td>0.9809</td>
<td>0.9703</td>
<td>0.9727</td>
</tr>
<tr>
<td>20</td>
<td>0.9750</td>
<td>0.7593</td>
<td>0.8496</td>
</tr>
<tr>
<td>25</td>
<td>0.9790</td>
<td>0.5955</td>
<td>0.7528</td>
</tr>
<tr>
<td>30</td>
<td>0.9780</td>
<td>0.5477</td>
<td>0.7073</td>
</tr>
</tbody>
</table>

From the table, it is observed that the maximum mean F1 measure of KBFNM model is 87% and the corresponding mean recall and precision are 77% and 97% respectively for top-N=10.
Comparison of Recall

Figure 6.7 shows mean Recall measure of various number N of recommendations calculated by KBFNM method. The x-axis shows the number of recommendations N and y-axis shows the mean Recall measure. This pictorial representation clearly shows that the maximum mean Recall value is obtained using Jester-3 for number of recommendations \textit{top-N}=10.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig6_7.png}
\caption{Mean Recall of top-N recommendations using Jester dataset}
\end{figure}
Comparison of Precision

Figure 6.8 shows mean precision measure of various number N of recommendations calculated by KBFNM model. The x-axis shows the number of recommendations N and y-axis shows the mean precision measure. This pictorial representation clearly shows that the maximum mean precision value is obtained using Jester-1 for number of recommendations top-N=10.

![Graph showing mean precision of top-N recommendations using Jester dataset](image)

*Fig 6.8 Mean Precision of top-N recommendations using Jester dataset*
Comparison of F1 Measure

Figure 6.9 shows mean F1 measure of various number N of recommendations calculated by KBFNM model. The x-axis shows the number of recommendations N and y-axis shows the mean F1 measure. This pictorial representation clearly shows that the maximum mean F1 value is obtained using Jester-3 for number of recommendations top-N=10.

Fig 6.9 Mean F1-Measure of top-N recommendations using Jester dataset
6.4.4 Comparison with Conventional Approaches

This section explains the comparison of KBFNM model with conventional k-Nearest Neighbour (k-NNBM) Approach[19][32][60][80] using MovieLens and Ant Based Recommender System (ARS) [62], k-nearest neighbour based Mean Squared Distance (MSD-CMB)[71] Jester datasets with commonly compared top-N value as 10.

Comparison using MovieLens dataset

The Table 6.5 shows the comparison of Mean F1 measure between KBFNM model and conventional models using MovieLens dataset for top-N=10.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>k-NNBM</th>
<th>k-NNBM(w)</th>
<th>GAC</th>
<th>k-NNBM(PCC)</th>
<th>KBFNM</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1 Measure</td>
<td>0.44</td>
<td>0.53</td>
<td>0.60</td>
<td>0.66</td>
<td>0.75</td>
</tr>
</tbody>
</table>

The results listed in the table shows that, the accuracy of KBFNM model is better than k-NNBM, k-NNBM (w), GAC and k-NNBM (PCC) algorithms. When compared with k-NNBM, k-NNBM (w), GAC and k-NNBM (PCC) algorithms minimum 9% increase in F1-measure is obtained using KBFNM model. Therefore the performance of the KBFNM is more significant than the conventional methods.
Comparison using Jester dataset

KBFNM model is compared with conventional recommender systems based on collaborative behaviour of Ants Recommender System (ARS) [62] and k-nearest neighbour based Mean Squared Distance (MSD-CMB)[71] using Jester dataset. The Table 6.6 shows the comparison of mean F1 measure between KBFNM model and conventional models using Jester dataset for top-N=10.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>ARS</th>
<th>MSD-CMB</th>
<th>KBFNM</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1 Measure</td>
<td>0.49</td>
<td>0.68</td>
<td>0.87</td>
</tr>
</tbody>
</table>

The results listed in the table shows that, when compared with ARS and MSD_CMB algorithms minimum 19% increase in F1-measure is obtained in KBFNM model. Therefore the performance of the KBFNM is more significant than the ARS and MSD_CMB methods since it gives more recommendation accuracy measured in terms of F1 measure.
The Table 6.7 shows that the sample list of top-10 movies recommended by knowledge based model for the active user with age=25 and gender = Male using MovieLens dataset.

<table>
<thead>
<tr>
<th>No</th>
<th>Movie Title</th>
<th>Release date</th>
<th>No</th>
<th>Movie Title</th>
<th>Release date</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Toy Story (1995)</td>
<td>01-Jan-95</td>
<td>6</td>
<td>Seven (Se7en) (1995)</td>
<td>01-Jan-95</td>
</tr>
<tr>
<td>3</td>
<td>Copycat (1995)</td>
<td>01-Jan-95</td>
<td>8</td>
<td>Postino, Il (1994)</td>
<td>01-Jan-94</td>
</tr>
<tr>
<td>4</td>
<td>Twelve Monkeys (1995)</td>
<td>01-Jan-95</td>
<td>9</td>
<td>Mr. Holland’s Opus (1995)</td>
<td>29-Jan-96</td>
</tr>
<tr>
<td>5</td>
<td>Dead Man Walking (1995)</td>
<td>01-Jan-95</td>
<td>10</td>
<td>Muppet Treasure Island (1996)</td>
<td>16-Feb-96</td>
</tr>
</tbody>
</table>
6.5 SUMMARY

In this chapter collaborative filtering approach based on the combination of soft computing technique such as fuzzy logic and neural network has been presented. The use of this hybrid approach joining the advantages of fuzzy logic and neural networks in order to develop CF recommender system that suggests items to the active user on the basis of crisp and/or fuzzy rules.. The implementation of neural networks for collaborative filtering recommendations was explained by an example real world dataset of movies and jokes rated by users. Results of a simulation study using various similarity measures and recommendation methods show that the KBFNM model performs better than other conventional techniques. The experimental results exhibit that modeling uncertainty using fuzzy logic and neural networks improves the performance of personalized recommender systems.