Implementation on Hybrid Recommendation System for Movie dataset

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Abstract- There is a subclass of information filtering system which is known as recommendation system. With the help of it, they make similarity between items and users. In the online social network they can be used as filtering tool. There is huge amount of data and the data contains items, these items are somehow connected to each other, Collaborative filtering recommendations are based on similarity of items, the items are compared with each other in the data set in order to find the similarity. There is huge amount of data in the dataset forthis calculation time is more. So the solution is that to group the data so it will easy to compare the data within the same group. Whenever used search in the past with the help of it there is filtering and recommendation is done. In this paper proposed hybrid technique for movie recommendation and also compare hybrid technique with content based filtering and collaborative filtering. Found that Proposed hybrid technique recommended movie more accurately and efficient.

Keywords- Recommendation system, content based filtering, collaborative filtering, similarity function**.**

I. INTRODUCTION

The system in which there is filtering of information based on past history is called as recommendation; it filters the data and recommends the items. Product is presented as they most like by the consumer, collaborative filtering is used for these. This is all done with the history of user information and all this data is only source key to recommend the any product or movie [1]. For recommendation of any product or data the system must go through some information like user data, user profile, it behavior, preferences and habit of users and comparison of the information to present the recommendations. It much trusts on comparison calculation.

Types of Recommendation System

There are three types of recommendation system ;

- Content-Based Filtering
- Collaborative Filtering
  - o Memory-Based or User Based Collaborative Filtering
  - o Model-Based or Item Based Collaborative Filtering
- Hybrid Recommendation Systems

Content-based filtering system recommendations have finite scope and require items and attributes to be machine-recognizable. It cannot filter items on some appraisal of quality, style or viewpoint because of lack of consideration of other people’s experience and also there is absence of personal recommendations. In content-based filtering system there is no unexpected items, i.e. Chance is the capability of the system to give an item surprisingly interesting to a user, but not expected by the user.

II. LITERATURE REVIEW

Theyproposed a hybrid model-based movie recommendation system that utilizes the improved K-means clustering coupled with genetic algorithms (GA) to partition transformed user space. By this proposed method it will capable of generating effective estimation of movie ratings for new users via traditional movierecommendation systems[1].

Authors provide a combinatorial approach by combining fuzzy c meansclustering technique and genetic algorithm based weighted similarity measure to develop a recommendation system (RS). The proposed FCMGENSM recommendation system provides better similarity metrics and quality than the ones provided by the existing GENSM recommendation system but the computation time taken by the proposed RS is more than the existing RS[2].

Theyproposed a novel modified fuzzy C- means clustering algorithm which is used for hybrid personalized recommendation system. There are two phase.In the first phase views from operators are composed in form of operator item grade matrix. In second phase references are generated online for active users using similarity measures [3].

Authorsproposed fuzzy weightings for the most common similarity measures for memory-based CRSs. Fuzzy weighting can be measured as a learning device for taking the favorites of users for ratings. Associating with genetic algorithm knowledge, fuzzy weighting is fast, real and does not need any more space. Experimental results show that fuzzy weighting improves the CRS performance irrespective of the fuzzy weighting variable where the fuzzy-weighted similarity measures outperform their traditional counterparts in terms of PCP, coverage, and mean absolute error[4].

Authors gave the review about the Recommendationsystems using collaborative filtering. It is the most general and positive method that indorses the item to the target user. Scalability is the major challenge of collaborative filtering. With regard to increasing customers and products gradually, the time consumed for finding nearest neighbor of target user or item increases, and consequently more response time is required [5].

They introduces a new hybrid recommendation system by exploiting a combination of collaborative filtering and content-based approaches in a way that resolves the drawbacks of each approach and makes a great development in the variation of recommendations in contrast to each individual approach. It introduces a new fuzzy clustering methodbuilt on genetic algorithms and creates a two-layer graph. [6].

They proposed fuzzy recommendation system based on collaborative behavior of ants (FARS). It works in two phases. The user's performances are showed offline and results are used in next phase for online recommendation. The performance is evaluated using log files.

III. EXISTING WORK

Collaborative filtering approaches often suffer from three problems:

- Cold start
- Scalability
- Sparsely

The collaborative filtering algorithm usagesmatrix factorization, a low-rank matrix approximationtechnique. There are two methods of collaborative filtering these are memory-based and model based collaborative filtering. A well-known example of memory-based approaches is user-based algorithm and that of model-based approaches is Kernel-Mapping Recommendation.

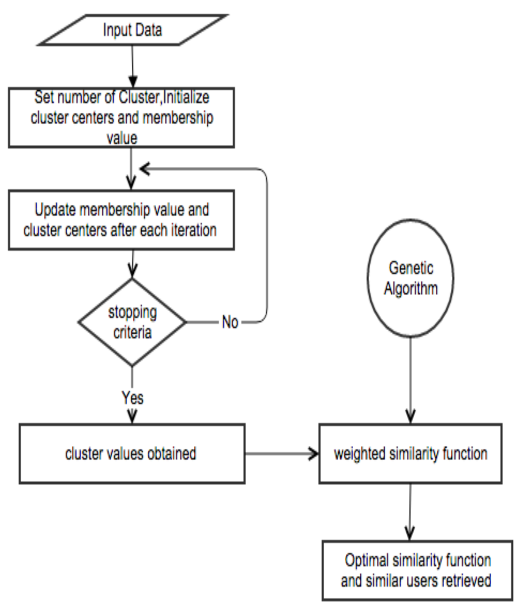

Fig.1: Flow chart of Collaborative Recommendation using Genetic Algorithm

IV. PROPOSED WORK

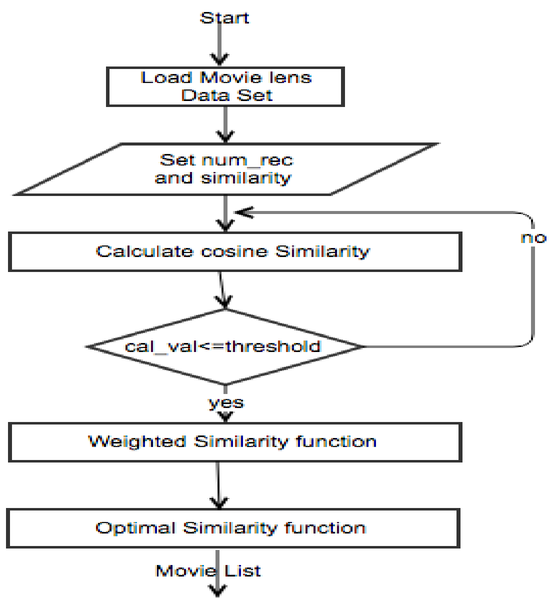

Fig.2: Flow chart of Proposed System

In the existing paper it is implemented on Movie lens datasets only. Proposed System will be implemented on the Movie lens database. To calculate the similarity between the different items in the given dataset in least time and efficiently and reduce computation time of the recommendation system we can use cosine similarity. It takes less execution time than other similarity measures like adjusted based similarity, correlation based similarity. On the basis of below equation compare existing and proposed system.

Accuracy

Accuracy is the part of true outcomesbetween the total numbers of cases observed.

$$accuracy = \frac{number\ of\ true\ positives + number\ of\ true\ negatives}{no.of\ true\ positives + false\ positives + false\ negatives + true\ negatives}$$

Cosine Similarity

The cosine-similarity between two users x and y are defining by cosine based approach:

$$\mathrm{simil}(x,y) = \cos(\vec{x},\vec{y}) = \frac{\vec{x}\cdot\vec{y}}{||\vec{x}|| \times ||\vec{y}||} = \frac{\sum_{i\in Ixy} r_{x,i} r_{y,i}}{\sqrt{\sum_{i\in I_x} r_{x,i}^2}\sqrt{\sum_{i\in I_y} r_{y,i}^2}}$$

Recall

The relevant document is retrieved in a search and it is randomly selected and its probability is recall.The fraction of the documents that are relevant to the query that are successfully retrieved is the recall in information retrieval.

$$\text{recall} = \frac{|\{\text{relevant documentd}\} \cap \{\text{retrieved documentd}\}|}{|\{\text{relevant document}\}|}$$

Precision

The fraction of retrieved documents that are relevant to the query is the precision:

$$precision = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|}$$

Mean Absolute Error

The quantity used to measure predictions are to the eventual outcomes is the mean absolute error. The mean absolute error is given by

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|fi - yi| = \frac{1}{n}\sum_{i=1}^{n}|ei|$$

The average of the absolute errors is the mean absolute error $|e_i| = |f_i - y_i|$,

$$|ei| = |fi - yi|$$

Where

f_i is the prediction

y_i the true value.

V. RESULT

We implemented set of experiments that show for evaluating the impact of proposed system on recommendation. We have done different experiments on the movie lens data set. In Currently, we have a tendency to perform experiments on Movie rating knowledge collected from theMovielens web-based recommendation system. The information set contained a 100,000 ratings from 943 users and one,682 movies, with every user rating a minimum of twenty things.

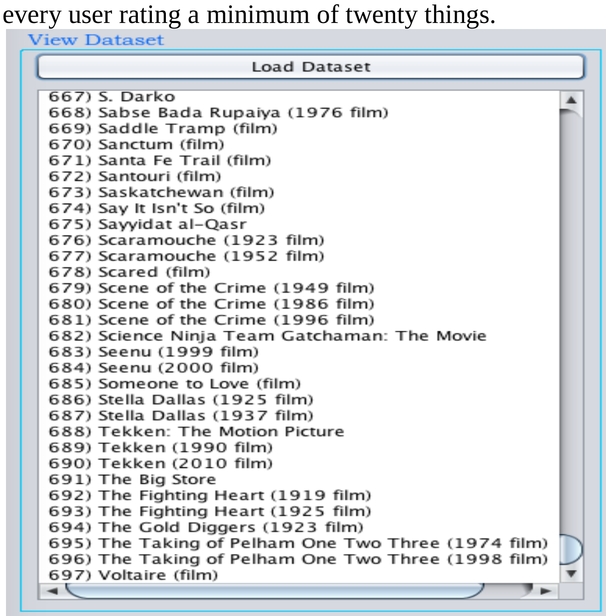

Fig.3: Movie lens dataset

In proposed system and existing system compare on the basis of following parameters.

1. Computation time
2. Accuracy

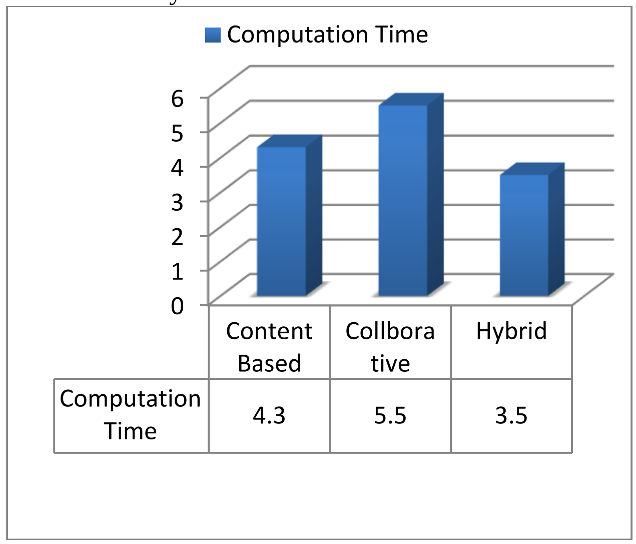

Fig.4: graph of computation time

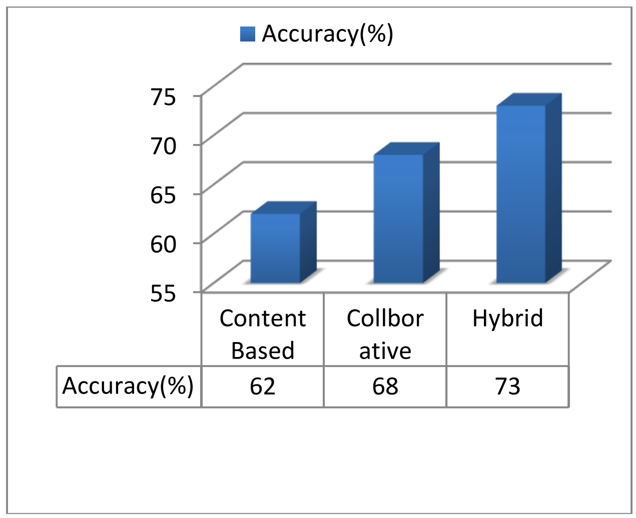

Fig.5: Graph of Accuracy

VI. CONCLUSIONS

Recommendation systems are a powerful new technology for extracting additional value for a business from its user databases. From these system user get help to buy the item. Recommendation systems benefit users by enabling them to find items they like. Thse will help in more sale and to grow the business.. Recommendation systems are rapidly becoming a crucial tool in E-commerce on the Web. Recommendation systems are being stressed by the huge volume of user data in existing corporate databases, and will be stressed even more by the increasing volume of user data available on the Web.

New technologies are needed that can dramatically improve the quality and scalability of recommendation systems.

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