A Novel Recommendation System Based on user Social Voting with Distance Matrix and NN

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Abstract - Recommender Systems are a product of research carried out in the field of Information Retrieval, particularly into Information Filtering techniques developed to better cope with the exponential growth of information in the computer age. This places Recommender Systems within the field of Data Mining and Machine Learning. In fact, Recommender Systems are said to "learn" the preferences of a particular user, with the intention of suggesting relevant not-yet seen items to this target user. Many of the current recommender systems are developed for simple and frequently purchased products like books and videos, by using collaborative-filtering and content-based recommender system approaches. These approaches are not suitable for Recommendation of Online Social Voting. This work proposed a Collaborative Filtering-Based Recommendation of Online Social Voting system based on Distance Matrix and Nearest Neighbour Recommendation system.

Keywords- - Recommender Systems, Online Social Voting, Collaborative Filtering, Data Mining, Distance Matrix Recommendation system.

I. INTRODUCTION

At present, Recommender Systems (RS), are extensively used to execute Web 2.0 services in light of Collaborative Filtering (CF). CF RS make expectations about the inclinations of every client in view of the inclinations of an arrangement of "comparable" clients. Along these lines, a trek to Canary Islands could be prescribed to a person who has appraised diverse goals in the Caribbean exceedingly, in view of the constructive appraisals about the occasion goal of "Canary Islands" of a critical number of people who additionally evaluated goals in the Caribbean exceptionally.

There are an expansive number of uses in light of, some of which are focused on the motion picture suggestion territory. The nature of the outcomes offered by a RS incredibly relies upon the nature of the outcomes gave by its CF stage; i.e. it is fundamental to be able to do sufficiently choosing the gathering of clients most like a given person.

that combine the information data and the foundation data to produce recommendations. In a real system, foundation data is the user profiles, and the info data are the activities the user performs to get a recommendation. This process is appeared in figure 1.1.

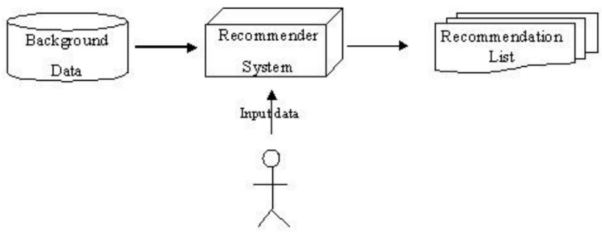

Figure 1.1 Recommenders system basic architecture.

The following types of filtering are usually used by RS:

- Content-Based Filtering: The recommendations depend on the clients' past decisions (i.e. proposal of another programming book to a client who bought different books regarding this matter the earlier year.
- Demographic filtering: The recommendations depend on the information gave by clients thought about comparable as indicated by statistic parameters, for example, age, sex, nationality, and so forth.
- Collaborative filtering: The recommendations for every client (active client) are acquired in accordance with the inclination of different clients who have evaluated the items (things) likewise to the dynamic client.
- Hybrid filtering: The recommendations are made by consolidating the past separating; specifically, Content-based sifting/CF and Demographic sifting/CF are utilized.

Among the three sorts of fundamental sifting (Content-based separating, Demographic sifting, CF), CF is the one that generally gives the best outcomes. CF ascertains the recommendations in light of the information of the votes that all clients have given a role as respects their inclinations on the things (i.e. in a film RS, the aggregate inclinations made by every client on each of the movies they have voted in favor of).

When the CF is exclusively in view of the information put away in the variety of votes it is called memory-based CF. An assortment of CF exists which acquires information from extra sources to the variety of votes, for example, the social relations between clients or the substance of posts in web journals; in these cases (memory-based+additional information) the extra information is utilized to enhance the nature of the recommendations, however its utilization is just pertinent to the subset of RS where that sort of extra information exists.

II. SYSTEM MODEL

The recommender system is the most useful way to help consumers to purchase products in an E-commerce (EC) system. The information generated from the experiences of past similar users in a traditional recommender system is called the objective information. This kind of information does not include the influence of domain experts or opinion leaders on the customers' purchasing decision. Consider the following scenario: someone goes to see a movie on Saturday; he will check the film review from many difference ways, such as: Yahoo movie and IMDB. Because the influence of domain expert on consumers is self-evident, it will be better if the opinion from domain expert can be involved in the recommender system [8]. Li-Chen Cheng et al . in 2011 proposed a novel A Novel Fuzzy Recommendation System [8] . the proposed algorithm which is similar in spirit to the classical memory-based CF approach.

The major algorithms applied in generating clusters are c-means referring to sharp clustering while fuzzy c-means refers fuzzy clustering. Therefore, the fuzzy recommender system prototype designed in the present study will be based on fuzzy c-means algorithm. The c- means for fuzzy clustering refers to algorithm cluster analysis method proposed by Bezdek (1981) targeting partitioning of n number of observations into c clusters. From each observation there must be only one cluster thus extension of fuzzy c-means allows c-means algorithms to accommodate graduate membership of data points into clusters of varying degree of membership in accordance to the fuzzy set theory.

the field of collaborative recommendation system still generates high interests because of the abundant practical implications of the systems driven by greater demand for personalized recommendation applications. The system recommendation protocol is sub-divided into 3 steps. The first step entails creation of individual profiles by candidates and voters (users) using fuzzy-interface tools. This is a convenient technique because the tools guides users in determining the levels of agree, disagree, and specific questions relevance. The generated fuzzy profiles are then stored in the Drupal database. The second step entails user selecting recommended targets once all profiles required have been generated and the output type (Top-N recommender, Political community or Fuzzy clustering). The last step, involves receiving recommendation by users once the recommender engine finishes computing all datasets into a pre-determined format Figure 3.1 bellow shows the fuzzy recommendation design. From the data flow presented, each element is linked based on Teran & Meier detailed recommendation engine.

The fuzzy-based recommender engine can also accommodate ePosting and eDiscussion therefore creating wide participation or better known as political communities. Such platform allows participating citizens to interact via social media and deliberating on specific issues. concerning their daily lives. The platform is not limited by political or geographical boundaries making it a versatile tool in pursuant of mutual goals or interests among participants. In conjunction with its user-friendly 2-dimensional interfacing, the recommender system is helpful to voters in determining which of the public members share similar views and interests as per their profiled tendencies or preferences.

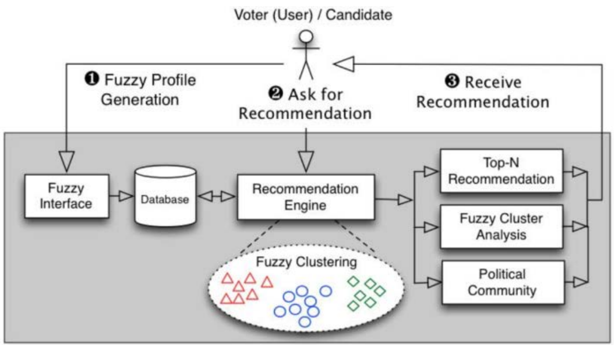

Figure 3.1.Fuzzy recommendation system.

III. PROPOSED METHODOLOGY

In the proposed work a semi structured dataset are used in that data set already having no of instances like users, ratings, and movies. In proposed work first find the probabilities of the ratings and users based on that are constructing distance matrix based on that are found in the nearest neighbors these two data points send to the recommender for recommendation.

Development of recommender systems is based on two different models: Collaborative Filtering (CF) and Content Based Filtering (CBF). The collaborative filtering model uses user evaluations on different items in prediction of unknown ratings for new user-item pairing. The CF algorithms typically are classified as factorization or neighborhood methods. The factorization algorithms are favorable because of their effectiveness compared to neighborhood algorithms. However the two methods often complement each other for achieving greater performance.

Addressing the needs of different group members requires fitting of their varied tastes by adopting a fuzzy based cluster algorithm. The model regroups participants/users according to their profile thus guaranteeing a multi-affection to nearest cluster. This allows the users to receive generated recommendations.

The system is based on clustering of user profile similarities with view of resolving the problem of scalability. Conventional recommender systems heavily relied on generation of inter-user similarities based on differences in their score ratings. The present study argues that use of variations in score similarities in itself is insufficient in generating effective and accurate recommendations. For this reason the study proposes introduction of entropy notion in raising the level trustworthy among users during generation of recommendations.

For easier analysis, the results are presented to users in a graphical representation by the recommender engine by simulation screen captures.

IV. SIMULATION OUTCOME

Synthesis and implementation of proposed work has done on Matlab 2011a .Evaluation of results of Proposed work has done by presenting Recall versus neighborhood size of top recommenders. Following are some key terms used during simulation of proposed recommendation system. Figure 4.1 t o figure 4.7 shows the simulation screen of proposed recommendation system.

> User Activity

The function "> User Activity" shows user participation on movies and ratings tasks.

> User Objectivity

The function "> User Objectivity" shows number of user interested on movies and user rated the movies.

> User Consistency

It shows user high and low Existnecyon movies and user rated the movies.

> Hot/NonHOT Votings

This function "> Hot/NonHOT Votings Shows "High voted / low voated based on their votings and reviews.

> Cold Users/ Heavy Users

The function > shows Cold Users/ Heavy Users Deviation of High voted /deviation of low voated with weight

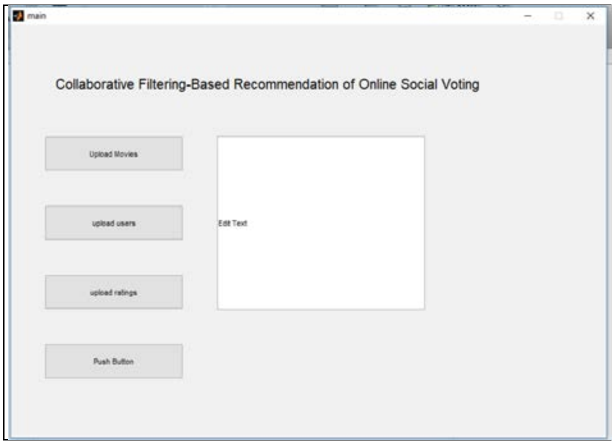

Figure 4.1 CF Based Recommendation system of Online Social Voting Simulation Screen.

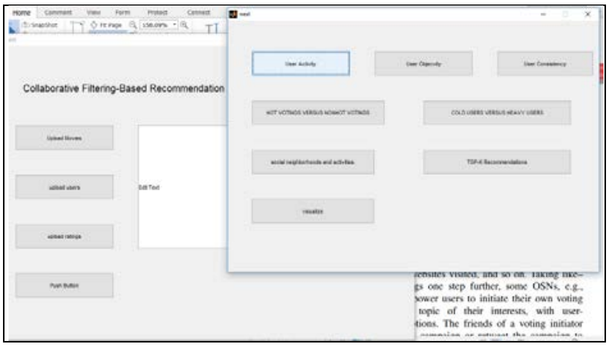

Figure 4.2 Activity Menu Screen.

```
>> clear
UseriD     Movie ID     Score Time  Stamp
    '16'     '2987'    [0.3302]    '978174795'
    '5'      '2987'    [0.3178]    '978243170'
    '11'     '1753'    [0.3051]    '978904024'
    '14'     '3354'    [0.3012]    '978200924'
    '15'     '3421'    [0.3009]    '978196170'
    '13'     '2987'    [0.2951]    '978202328'
    '2'      '1357'    [0.2693]    '978298709'
    '9'      '2268'    [0.2677]    '978226495'
    '18'     '2987'    [0.2644]    '978154285'
    '12'     '1252'    [0.2614]    '978220237'
    '8'      '39'      [0.2574]    '978229571'
    '6'      '2406'    [0.2563]    '978236670'
    '3'      '3421'    [0.2563]    '978298147'
    '17'     '1179'    [0.2453]    '978160157'
    '10'     '2622'    [0.2430]    '978228212'
    '1'      '1193'    [0.2387]    '978300760'
    '4'      '3468'    [0.2386]    '978294008'
    '7'      '648'     [0.2313]    '978234737'

fx >>
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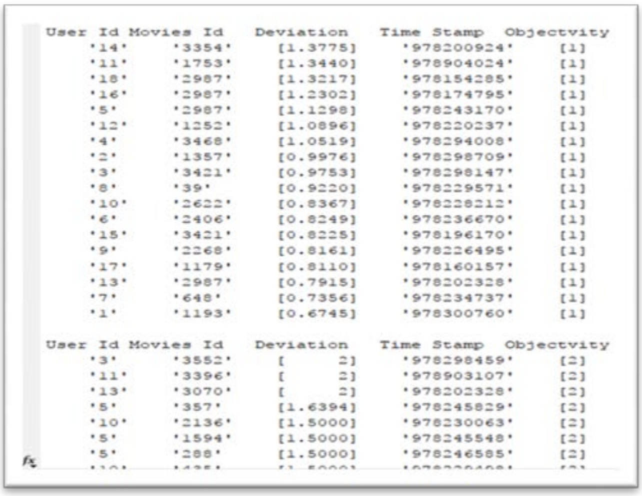
Figure 4.3 User Activity Log Screen.

Figure 4.4 User objectivity Selection Screen.



User Id	Movies Id	Deviation	Time Stamp	Objectvity
'14'	'3354'	[1.3775]	'978200924'	[1]
'11'	'1753'	[1.3440]	'978904024'	[1]
'18'	'2987'	[1.3217]	'978154285'	[1]
'16'	'2987'	[1.2302]	'978174795'	[1]
'5'	'2987'	[1.1298]	'978243170'	[1]
'12'	'1252'	[1.0896]	'978220237'	[1]
'4'	'3468'	[1.0519]	'978294008'	[1]
'2'	'1357'	[0.9976]	'978298709'	[1]
'3'	'3421'	[0.9753]	'978298147'	[1]
'8'	'39'	[0.9220]	'978229571'	[1]
'10'	'2622'	[0.8367]	'978228212'	[1]
'6'	'2406'	[0.8249]	'978236670'	[1]
'15'	'3421'	[0.8225]	'978196170'	[1]
'9'	'2268'	[0.8161]	'978226495'	[1]
'17'	'1179'	[0.8110]	'978160157'	[1]
'13'	'2987'	[0.7915]	'978202328'	[1]
'7'	'648'	[0.7356]	'978234737'	[1]
'1'	'1193'	[0.6745]	'978300760'	[1]

User Id	Movies Id	Deviation	Time Stamp	Objectvity
'3'	'3552'	[2]	'978298459'	[2]
'11'	'3396'	[2]	'978903107'	[2]
'13'	'3070'	[2]	'978202328'	[2]
'5'	'357'	[1.6394]	'978245829'	[2]
'10'	'2136'	[1.5000]	'978230063'	[2]
'5'	'1594'	[1.5000]	'978245548'	[2]
'5'	'288'	[1.5000]	'978246585'	[2]

Figure 4.5 User Objectivity Log Screen.

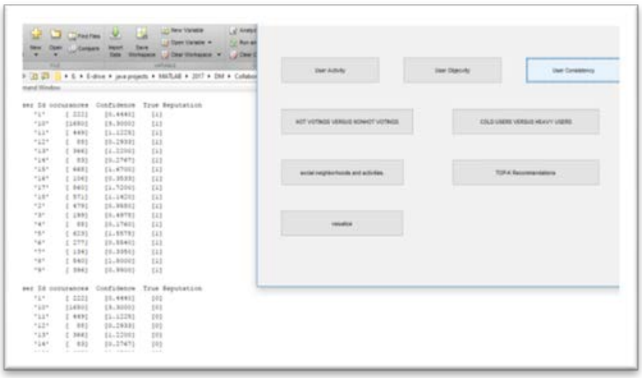


Figure 4.6 User Consistency Selection Screen.

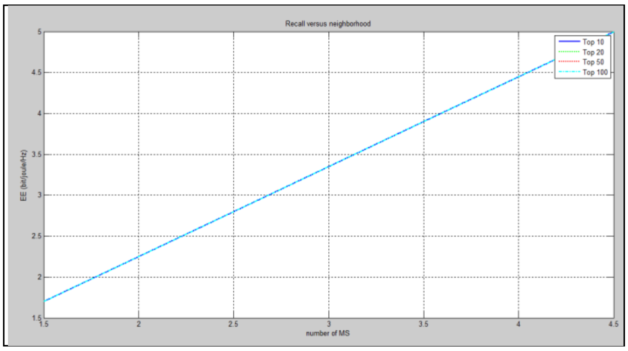


Figure 5.7 Recall versus neighborhood plot.

V. CONCLUSION

In the recent past, social scientists and economic scholars have attempted to bridge the existing gaps between technological advances, its applications, and public participation. E- participation is rooted deeply in such research trends and is conceivable as a platform with broad, all-inclusive, and collaborative process incorporating sets of standards and tools that stimulate public participation. The present study proposed Collaborative Filtering-Based Recommendation of Online Social Voting by using fuzzy logic based recommendation system. The proposed work has been implemented and simulated on Matlab 2011a. prototype system was designed and implemented online to stimulate citizenry participation in policy formulation and decision making. The performance of proposed system has been evaluated and on matlab simulator Isim.

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