International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-9 Issue-1, October, 2019

Ontology Based Recommender System using Fuzzy Clustering Technique

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Abstract: ***Recommender systems (RS) are the agents of information filtering processes. With a myriad of data in the world wide web, reaching the exact entity of interest is the need of the hour. Collaborative filtering is a type of RS concerned with studying past data to predict assumptions for the future. In this work, the collaborative filtering recommender is improved by incorporating ontology and fuzzy clustering algorithms to provide ranked recommendations. Ontology models semantic information from raw natural language data to better represent domain knowledge and user preferences. In this way, data sparsity problem could be sorted. The proposed recommender framework runs on top of a historical data that is not only semantic but also represents users preferences perfectly. Another problem of cold start can also be solved by including maximum expectation strategy by constructing the user ontology and domain ontology separately and mapping it to achieve a unified recommender ontology. Using fuzzy clustering introduce a degree of membership for each user with their interests. It also allows for attributes to be distributed in more than one cluster, thus enabling users to be clustered in the most inclusive manner possible. Which provides for ranked recommendations that represent diversified interests of a single user. The dynamic framework is compared with baseline models. Experimental results have shown significant improvement in the recommendation accuracy.***

Keywords : Text categorization, Recommender system, Fuzzy clustering, Ontology, Knowledge discovery, Feature extraction.

I. INTRODUCTION

Wherever the users are interacting with a system, there is need for a information filtering system in other words recommender system. A recommender system [1]acts as human assistant in suggesting items of interests to a particular group of users. Each group of users will have a different suggestion. Some of the famous applications of recommender systems are Amazon, Netflix, ebay etc. They study the customer behavior to analyze their needs and predict the product of their choice. For example, customers who bought item a, also bought item b. It works on the basis of frequently co-occurring patterns. The user item inter-action can be represented better in using ontology. Since, an ontology is inherently a tool for extracting relationship between entities.

Revised Manuscript Received on October 30, 2019.

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It is the representation of shared knowledge in a conceptual manner. When the number of user-item pairs increases it becomes difficult for the traditional data management tools to handle. Ontology [2] is helpful in many ways like, knowledge processing, separating application knowledge from domain knowledge using relationships, properties and classes. It acts the foundation of semantic web. Therefore we have used ontology to achieve this recommender system. To build effective ontology for both domain and user_profile the data about both are collected and feature engineered. Feature extraction [3] or selection refers to the process of manually or automatic selection of features that better represent the target class. Also keeping the unrelated features will result in model getting slower and biased and inaccurate. In order to avoid these we employ feature selection to improve algorithm performance. Some of the benefits of feature selection are, reducing overfitting, accuracy improvement and training time reduction. This work uses boruta feature selection technique to achieve feature selection. It is an all inclusive algorithm that has shadow features and random forest algorithm to provide the best feature subset. Finally for building the recommender data model [4] Fuzzy Clustering Mean algorithm is used. It clusters user groups that are highly similar. It also has variety of similarity measures to improve clustering such as, distance, intensity and connectivity. It has a degree of fuzzyness with each class member which helps to soft cluster a user into multiple groups. Which again improves recommendations s two or more users will have interests in multiple items. This technique also proves to be useful for ranking the recommendations to the users. Ranking is the novel feature of any recommender system, where the user is not concerned about every item available. For ranking recommendations vector space model is used to provide top-N suggestion to the users. The remainder of the work is structured as follows: Section 2 describes the literature review undertaken for studying recommendation systems and fuzzy ontologies. Section 3 describes the methodology proposed and how the domain ontology and user_profile ontology are built and ranked recommendations are provided. In Section 4 the experimental evaluation of various tests conducted to validate our proposal are explained and displayed, and in Section 5 describes the conclusions and future works related to ontology based intelligent recommender systems.

II. LITERATURE REVIEW

Recommender systems help users find products of their choice by giving them customized suggestions among the huge item space. They in fact calculate a level of similarity between so many groups such as, user-user, user-item, item-item etc.

Based on the similarities they give predictions for unseen items and new users. A type of recommender system[5] integrated ontological knowledge for providing suggestions, however the recommendations were complex and suffered from circumstances issues. It also failed to solve the cold start problem.

Applications of the recommender systems in healthcare environments is taken up seriously in the recent years, for example, a personalized healthcare application that monitors health events and suggest precautionary measures in a personalized manner [6]. It makes use of a group of "signal definitions", which means a set of predefined structured queries with all parameters related to kinds of health threats of the particular users' are studied. The system provided ratings for individual health events and user based on the "signal definitions" to give recommendations. However, this technique suffered from data dimensionality failed for large queries. It used tf-idf and similarity was measured using cosine metrics but results were not satisfactory.

Incorporating fuzzyness in recommendation is an interesting research direction . Proposed a recommender mechanism for teachers to chose relevant content. This is named as content management system. It used association rule [7] based classification, sequential pattern mining technique, and fuzzy sets to achieve the course recommendations. This model suffered from time complexity due to usage of multiple algorithms and techniques to suggest recommendations. Also, the feature set was ineffective to achieve model performance improvement.

From the review of the literature, a few research gaps have been identified with respect to ontology based intelligent recommender system mechanisms are given below:

Problems Identified:

1. Lack of Data (cold start problem) as in some scenario, the data or rating for a particular entity will not be available.
2. Changing User Preferences as users change constantly with time. Therefore, the model needs to be scalable to accommodate changes in periodic intervals
3. Unpredictable Items appear in some cases where, some items cannot be recommended to any users.
4. Scalability of the domain information with addition of new knowledge as in our case the unified ontology has to be scalable.

The aim of this work is to solve the above issues optimally.

III. PROPOSED METHODOLOGY

The proposed framework is named as OBIRS, Ontology Based Intelligent Recommender System. It aims to construct a semantic recommender system[8] that has knowledge about the users and their associations in the form of unified ontology that was obtained after merging the user and domain ontologies, which will become the training data. This data will be fed as input to build a machine learning data model. This data model clusters similar user profiles using fuzzy clustering mean algorithm. The recommendations are improved by the data model and ontology. As it provided semantically similar user profiles which also improves the traditional collaborative filtering approach. Finally, vector space model is used to rank the recommendations per user criteria. This provides users with top-N recommendations for a particular query. The architecture is given in Fig.1.

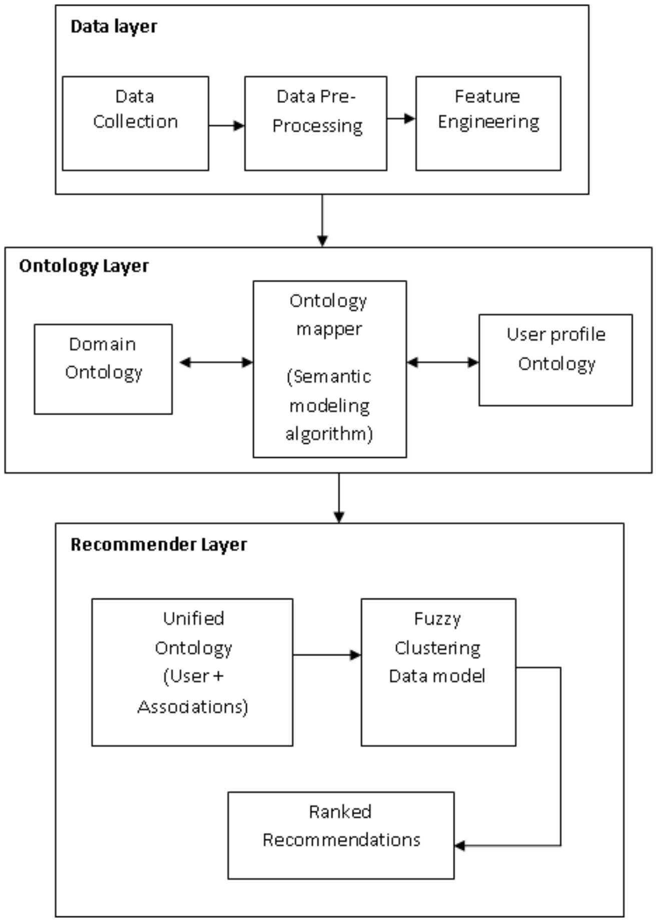

Fig.1 OBIRS: Ontology Based Intelligent Recommender System

Data Collection

In the data collection step, data about knowledge of the domain of interest and user preference data or other information related to users will be collected. It is done using web crawlers and web scrapers constructed in python. Knowledge acquisition is an important step for building effective ontologies. it leads to better conceptualization and better integration of various domain information.

Data Preprocessing

The data collected is in natural language format which cannot be analyzed by a machine. It will be preprocessed to convert the data to a structured format, more suitable for data analysis. This procedure is also called as text normalization where data from different sources and formats are converted to a single uniform format readable by the data model. This work used preprocessing techniques such as, stop words removal, lemmatization, stemming, and tokenization. The preprocessed data is fed into the feature engineering module.

Feature Engineering

To discriminate between the relevant and irrelevant parts of the data corpus, the features that better represent the population has to be filtered. This process is called feature extraction[9] also called feature engineering. It solves the dimensionality problem.

The set of features is denoted as, $F_1 = \{ f1_x ,\dots, fi_z ,\dots, f_x \}$ that maximizes the models ability to extract the subset of features that will improve the learner's capability to accurately classify categories. It will improve the scoring function of the data model. The optimal feature subset obtained will improve algorithm performance and also provide accurate results. Boruta feature selection algorithm is taken up for this study. it acts as a kind of wrapper algorithm around the Random Forest algorithm. It randomizes the dataset by shuffling feature copies in the form of shadow features. It uses the shadow features to train the random forest algorithm with a feature importance score. This score denotes different scores for different features based on their role in classification. And features that obtain least scores than others will be discarded and a subset with only eligible features is formed. When all the features are assigned scores and seggregated, the algorithm ends. Boruta is a highly inclusive technique that includes all possible features for the study. Whereas most of the [10]traditional feature selection algorithms adopt a minimum optimal method to pick only certain features for the study to reduce the error rate.

Domain Ontology

Once the most relevant features are obtained from the data layer, they are fed into the [11]ontology to construct two different ontologies. One is domain ontology and the other one is the User_Profile ontology . This ontology is built to improve the coherence of a domain knowledge and lexically relevant terms to a decision support system. To design the ontology languages like Resource description framework and web ontology language are used. For this work we manually built the ontologies using protege tool.

The domain ontology construction happens with specification of all the relevant concepts of the domain of interest. Since, we have taken up healthcare domain to test the architecture, data about various diseases, symptoms, causes, deficiencies, conditions, behavior impacts were gathered and processed in the previous phase. The feature set is fed into the ontology using java interface to build ontology from CSV files. The feature set contains more than 5000 features and their inter-relationships. Once the features are modeled into the ontology editor, it is manually verified to identify the presence of classes of interests.

To enhance the performance of the proposed system, accuracy of information in each class if verified. Consistency of different values without any impactful conflicts are analyzed. Then, the completeness of the information is checked and verified whether every item is represented fully in the ontology. Finally, the timeliness of information is checked to ascertain that no out-dated information is fed into the system also the temporal context of requirement is fulfilled.

User_Profile Ontology

The knowledge base of a recommender system is not complete without information about users or target end users. This knowledge if available for users from various demographic [12]features will prove to be the most effective tool for a recommender system. To model the real world characteristics of users taken up for this study, a User_Profile ontology is constructed. Every user has three main characters, their personal information, their interests and their abilities.

The manually built User_ Profile ontology has properties like, hasKids, hasAbility: bikes, hasPaymentoptions : debitcards, etc., When building this ontology we took 79 such properties to represent a person. The key terms for describing a user are identified and constructed as ontological classes as shown in Table 1. For example, the "New_User" class would contain a property called "Physically-disabled" to determine the state of a user's physical condition and also could be linked to the class "Capability". This would therefore determine that a user has a particular health condition such as polio, and could be inferred that they will have immobility of varying degrees.

Table 1. Sample User Profile Ontology with Top Level Classes

Name of Classes	*Description*	*SmapleValues*
New_User	Types of users involved.	"Physically-disabled", "Normal"
User_Profiles	Every user has atleast one user profile.	
Activities	User activities, social and work related.	"Reading", "Writing"
Activity_types	The types of activities the user are involved in.	"working" "athome", "traveller"
Health_Condition	The various health conditions.	"Thyroid", "Headache"
Health_Levels	The current health status of users.	"Mild", "medium", "Severe"
Locations	Where the user in located.	"House", "hotel", "school"
Timeframes	The time of days associated.	"Morning", "Evening"
Contexts	The environment of the user.	"", "college", "Home"

Semantic Mapper

The ontology mapping also known as merging approach[13] is based on word and context similarity(WCONS) .It is possible to map to different ontologies when the concepts in both ontologies have highly similar words but lower context similarity. Else, they should have least word similarity and more context similarity. Given a certain concept $d_{2u} \in N_1$, It is possible to eliminate concepts in ontology N_2 with semantic similarity value lower than the cut-off threshold values.The remaining concepts of ontology N_2, we obtain the concept d_{2x} which has the highest semantic similarity as mapping concepts to d_{2u}. The equivalence relation between concepts from User_profile ontology and domain ontology are calculated using Levenshtein distance[14].

Unified Ontology

Ontology Merging refers to building an ontology by combining the knowledge of two or more ontologies into one. The algorithm for merging two ontologies is given in previous section. In this work, the second ontology i.e. 'USER_PROFILE' Ontology is merged onto the first ontology i.e.' DOMAIN', to get the resultant merged domain-user ontology. This resultant merged domain-user ontology will have 'DISEASES', 'TREATMENT','CONDITIONS', 'SYMPTOMS' along with 'PERSON' as classes.

Fuzzy clustering Algorithm

The unified ontology obtained from the previous step is fed as training data into the Fuzzy Clustering Mean(FCM) algorithm . A data model is built for the recommender system using the existing machine learning algorithm . It revolves around the idea of membership between user features and item features.

The representation of entire domain along with user preferences, in the form of unified ontology provides a wider view of the recommendation requirements. The working of the algorithm is given in the text box.

> "It obtains matrix M of all cluster centers with membership matrix Q of similarity.
>
> It decides the total number of clusters, and construct fuzzy index O which is customizable. The membership matrix is initialized to first cluster center T. A
>
> Cluster center matrix is newly formed from the derivations.
>
> Euclidean distance between matrix samples and cluster centers are calculated and formed as matrix B.
>
> It has to be verified that the target value function is changed and iterations are stopped and fuzzy clusters are formed according to the membership matrix."

Ranking prediction

Ranking is the most important aspect of this recommender system. As a measure of information filtering, suggesting the top-N recommendations[15] to the user is highly expected. For achieving this we have used, Vector space model which is fundamentally an algebraic model used in information retrieval (IR). It depends on the domain features and user profile features and considers them as bag of words despite the inherent grammar formalities and word order. Since, the data is already in the form Of feature vectors after applying FCM in ontology, TF-IDF score can be readily calculated.

There are two uniqueness of this approach ,firstly, the model could be tailored to suit the various needs of a RS. Secondly, similarity between the neighboring users is already modeled in the clustering phase. Therefore, it is enough to apply a greedy method to aggregate the entire rankings of user-item pairs. The recommendations are ranked to a user based on the top-N items of the users belonging to the same cluster. The soft clustering in the previous phase also improved the ranking predictions.

It is also important to improve item ranking than ranking prediction. To solve this issue, a measure called Normalized Discounted Cumulative Gain(NDCG) is used. It is calculated for the top n items on the ranked list. It uses a normalization factor that maximizes NDCG value. It follows the notion that users with opposite similarities will have opposite interests called negative similarity.

The table 2 shows the performance of proposed model OBIRS compared with Baseline models like Memory Based Collaborative Filtering(MBCF) and Model Based Collaborative Filtering(MoBCF). The negative similarity values were calculated to test the efficiency of ranking items. For values 1,2,..5 the NDCG has achieved optimal performance for the proposed system.

Table 2.Model Ranking Performance

Model Name	NDCG@1	NDCG@2	NDCG@3	NDCG@4	NDCG@5
OBIRS	0.941526	0.922401	0.956457	0.970006	0.940537
MoBCF	0.821478	0.801547	0.800157	0.721763	0.801271
MBCF	0.800145	0.784512	0.874159	0.894125	0.794710

IV. EVALUATION RESULTS

The ontology based recommender system using fuzzy clustering technique is tested with a data corpus. A total of 7234 documents related to various diseases, its symptoms, conditions and demographic details are collected. User data was collected from hospitals and primary health centers. A total of 1350 different users with various ailments were collected. Along with this PubMed datasets were used improve data representation and to solve the problem of insufficient data in RS. The system was implemented with Jupyter notebook and Python environment using Ubuntu OS version 18.04.

The experiments aimed to optimize different parameters of the proposed method. The OBIRS was compared with baseline models like Memory Based Collaborative Filtering(MBCF)[2] and Model Based Collaborative Filtering (MoBCF)[3]. And also benchmark algorithms Co-Clustering, K-Means, kNN with Z score, Singular Value Decomposition(SVD), Naive Bayes and Perceptron were compared with FCM to ascertain the robustness of the model with different algorithms.

The accuracy of recommender system is usually evaluated through two important metrics, Root Mean Square Error(RMSE) and Mean Absolute Error(MAE). Depending on the various contextual requirements, one or both of them could be used.

Root Mean Square Error - For our experiments, we have used RMSE since MAE overlooks outliers. RMSE on the other hand though reflect every outlier in the data, it could be normalized when enough data is input for tuning the error set. RMSE formula is given as equation 2, where n is the number of samples and d is the observations and f is the predictions.

$$RMSE = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}\left(\frac{d_i - f_i}{\sigma_i}\right)^2} \quad \text{............(2)}$$

The final RMSE value obtained is 52.976543 this value shows the OBIRS model neither overfits the data nor allowing outliers. The RMSE comparison with baseline models is given in figure 2.

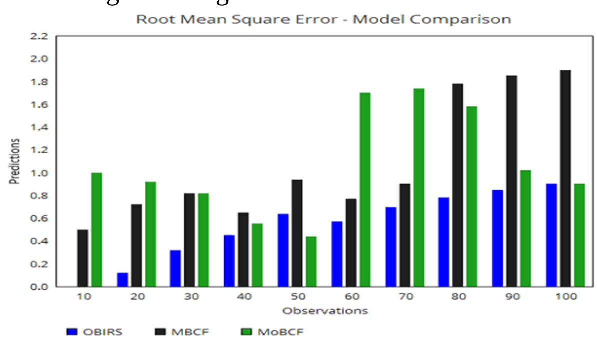

Fig 2. RMSE model comparison

From the figure 2 it is evident that the MBCF and MoBCF models overfitted data given and also in some instances, outliers have been accepted as true predictions. This shows that the proposed model is less prone to errors. This is due to the highly representative data being fed to the system by the ontology layer.

Overall accuracy obtained from recommender system feedback are denoted by precision, recall and f-measure. For evaluating the efficiency of the proposed system Mean Average Precision(MAP), Recall @k, F-Score@k are calculated

Mean Average Precision (MAP) - The formula for MAP is given as equation (3). Q is the total number of queries in the set and AveP(q) is called the average precision for some query, which is nothing but, average precision obtained for a set of queries. It is basically a product of precision and recall. Table 3.shows the comparison of OBIRS, MBCF and MoBCF [16]frameworks in terms of Recall, Fscore and Mean average precision is the varying window width with dimensionality d = 8. From the table 3, the MAP value obtained for OBIRS has shown significant improvement in terms of different dimensionalities. As the number of k value increases, the precision score is also increasing.

$$\mathrm{MAP} = \frac{\sum_{q=1}^{Q} \mathrm{AveP(q)}}{Q} \qquad \text{...........................(3)}$$

Recall @ k - Precision and Recall are termed as binary metrics that aims to evaluate models with binary outputs. When recommending the most probable items to the end user, it is important to calculate precision and recall for most probable user-item pairs. This is done instead of comparing every user item pair in the database. Therefore, a 'k ' value is set for top-n user item pairs. It could be customized in any number of ways according to the requirement. For our experiments, we have taken k values as 1,2,5 and 10 respectively for calculating precision. The formula is given in equation (4). From the table 3 it is seen that the proposed architecture achieves an average recall of 50% which is highly valuable for recommender systems. When there are no relevant items to suggest the recall value is set as k=1 by default.

$$\textbf{Recall} = \frac{\text{True Positive}}{\text{Predicted Results}} \text{ or } \frac{\text{True Positive}}{\text{True Positive + False Negative}} \qquad \text{.....(4)}$$

F1-score @ k- It is to calculated to optimally combine precision and recall. It takes the harmonic mean precision and recall as shown in the equation (5).F-score value for corresponding precision and recall values for various k values is listed in table 3.The F-score value has improved significantly when the top-10 recommendations are calculated.

$$F_1 = 2 * \frac{precision * recall}{precision + recall} \qquad \text{.......... (5)}$$

Table 3. Performance metrics analysis of the proposed architecture

Methods	n	recall@1	recall@2	recall@5	recall@10	F1-score@1	F1-score@2	F1-score@5	F1-score@10	MAP
MoBCF	2	0.0067	0.0103	0.0333	0.0508	0.0067	0.0069	0.0111	0.0093	0.6377
	3	0.0070	0.0104	0.0334	0.0510	0.0070	0.0070	0.0111	0.0093	0.7381
	4	0.0070	0.0107	0.0338	0.0520	0.0070	0.0072	0.0113	0.0095	0.5385
	5	0.0070	0.0108	0.0343	0.0527	0.0070	0.0072	0.0114	0.0096	0.8386
	6	0.0071	0.0112	0.0354	0.0538	0.0071	0.0074	0.0118	0.0098	0.8395
	7	0.0070	0.0111	0.0354	0.0543	0.0070	0.0074	0.0118	0.0099	0.9393
	8	0.0070	0.0108	0.0351	0.0535	0.0070	0.0072	0.0117	0.0097	0.8390
OBIRS	2	0.0070	0.0106	0.0343	0.0529	0.0070	0.0071	0.0114	0.0096	0.9388
	3	0.0071	0.0105	0.0338	0.0523	0.0071	0.0071	0.0113	0.0094	0.9385
	4	0.0071	0.0108	0.0337	0.0522	0.0071	0.0073	0.0113	0.0095	0.8388
	5	0.0070	0.0110	0.0366	0.0553	0.0068	0.0074	0.0123	0.0101	0.9396
	6	0.0072	0.0115	0.0372	0.0554	0.0072	0.0076	0.0124	0.0101	0.8404
	7	0.0070	0.0115	0.0362	0.0549	0.0070	0.0076	0.0121	0.0100	0.9798
	8	0.0070	0.0110	0.0348	0.0539	0.0070	0.0073	0.0118	0.0100	0.9892
MBCF	2	0.0057	0.0095	0.0323	0.0520	0.0055	0.0059	0.0110	0.0083	0.7356
	3	0.0060	0.0100	0.300	0.0510	0.0062	0.0062	0.0105	0.0087	0.8360
	4	0.0050	0.0101	0.0321	0.0522	0.0045	0.0070	0.0111	0.0085	0.9074
	5	0.0039	0.0098	0.0314	0.0507	0.0063	0.0068	0.0100	0.0092	0.6306
	6	0.0069	0.0056	0.0302	0.0510	0.0070	0.0070	0.0114	0.0090	0.6319
	7	0.0066	0.0101	0.0335	0.0500	0.0059	0.0073	0.0112	0.0094	0.8351
	8	0.0058	0.0085	0.0311	0.0515	0.0064	0.0072	0.0115	0.0091	0.8320

Accuracy - It is the measure of achieving recommendations that satisfy a user to certain level. When the accuracy is improved, the decision making becomes error free and also rational. It is the fraction of predictions obtained right by the proposed model. The formula is given in equation (6), where TP, TN, FP, Fn are True Positives, True Negatives, False Positives, and False Negatives respectively.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \qquad \text{.......................(6)}$$

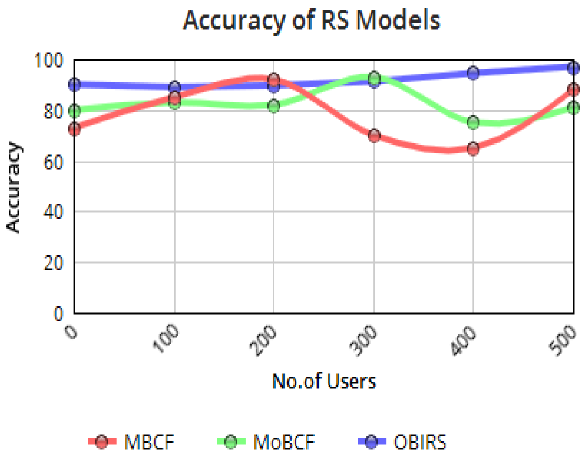

Fig 3. Accuracy of RS models

From the figure 3 the accuracy of proposed models with two baseline models can be seen. The proposed system achieves an average accuracy of 95% which is a significant improvement when compared to other two models. As, the performance of baseline models fell for more number of users.

Coverage - This is one more interesting metric for analyzing the potential of a recommender system. It is the coverage of a recommender over the percentage of items present in the recommendation domain. This work used prediction coverage[17] to evaluate the fitness of the model. Since, it is depended on the input data alone. When the input is enough, the coverage will be more.

It is the ratio between, percentage of items available for recommendation and percentage of items that are ever recommended to a user. Figure 4 compares the coverage achieved in various RS models. Though the model based collaborative filtering achieved a coverage of 90% for the two datasets PubMed and MeSh, the proposed system achieved a near perfect coverage in both datasets.

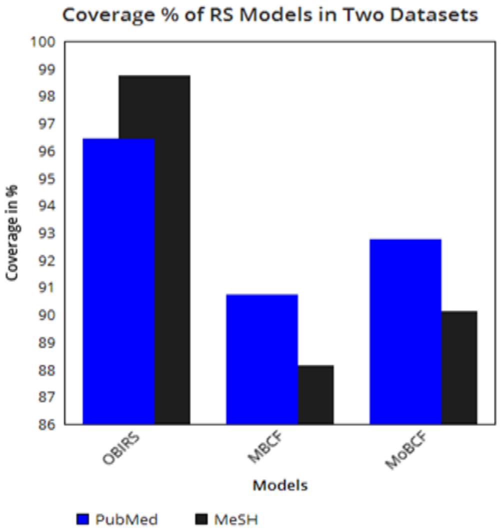

Fig 4. Comparison of coverage of various RS Models

Finally, the robustness of the model is tested with various benchmark algorithms based on the time taken by the model in fit_time, test_RMSE and test_time. In figure 5, the various standard algorithms like, Co-Clustering, k-Means, kNN with z score, SVD, Naive Bayes and Perceptron are compared with the Fuzzy clustering algorithm.

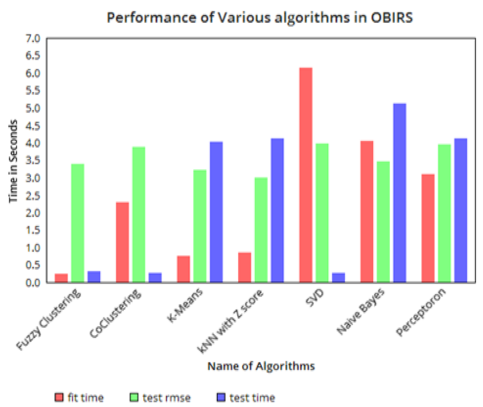

Fig. 5. Performance of standard algorithms in the proposed architecture

From the figure 5, it is clear that, the model fit_time and test_time are both optimal in FCM compared to others. Test_RMSE is the time required to test the model to find out the RMSE values, which has taken an average time of 3 seconds in almost all the algorithms which is negligible for a recommender system. Since, accuracy and robustness is the primary aim of any system FCM is the best alternative for this kind of system as it fits well ahead of time than all the other algorithms.

V. CONCLUSION

The need for semantically rich applications is increasing in the coming years. This framework is a step towards achieving smarter decisions that saves time and also suggest customized preferences. Clustering similar users preferences in the soft clustering mode also provides flexibility in the model to achieve accurate recommendations. This proposed work is for offline analysis of user interests where the prediction techniques used, gathers knowledge about user preferences and generalizes them over the domain. This technique generalizes user categories based on the feedback and the knowledge is used for future suggestions when a new user or new entity is introduced. Since, the user item matrix is represented as ontology scalability of model is achieved. The sub-clusters obtained from the FCM algorithm extract precise user groups with their interests. This framework can be applied to any domain as it is converted into a recommender data model. The fuzzyness measures the degree of global trust metrics of users in multiple clusters, providing for diverse recommendations. Using this kind of architecture for RS has shown an accuracy of 95% than which is a remarkable improvement compared to baseline models. The experiments, using the PubMed dataset and the crawled data corpus, proved that our method provides a comparable performance to the baseline in terms of precision, recall and fscores and RMSE. In future, more ways to automate ontology construction with additional feature engineering techniques could be investigated.

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