Optimal Rough Fuzzy Clustering for User Profile Ontology based Web Page Recommendation Analysis

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Abstract. Personalized information recommendation in view of social labeling is a hot issue in the scholarly community and this web page data collected from the Internet of Things (IoT). To accomplish personalized web pages, the current investigation proposes a recommendation framework with two methodologies on user access behavior using Rough-Fuzzy Clustering (RFC) technique. In this paper, Fuzzy-based Web Page Recommendation (WPR) framework is provided with the user profile and ontology design. At first, the weblog documents were gathered from IoT to clean the data and undergo learning process. In the profile ontology module, the learner profile was spared as the ontology with an obvious structure and data. For identification of the similar data, innovative similarity measure was considered and for effective WPR process, the generated rules in RFC were optimized with the help of Chicken Swarm Optimization (CSO) technique. Finally, these optimal rules-based output recommends e-commence shopping websites with better performances. A group of randomly-selected users was isolated and on the basis of the obtained data, their clustering was performed by cluster analysis. Based on the current proposed model, the results were analyzed with performance measures and a number of top recommended pages were provided to users compared to existing clustering techniques.

Keywords: Recommendation, Clustering, Rough Fuzzy, Optimization, Web Page, Products, Ontology.

1. Introduction

The quick development of the World Wide Web (WWW) postures uncommon scaling challenges for web indexes. In advanced time of high-volume information age, web indexes turn out to be a crucial innovation of data mining and information recovery [1].The IoT is a larger social network, connecting people to people, people to objects, and objects to objects [29]. The perusing examples of the users can

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assist associations with recommendations for the most important web pages as per the present interests of the users [2]. Web search tools are the most famous devices to find valuable information about a subject of intrigue. What makes web indexes well known is its direct and common way, by means of which individuals cooperate with it [3]. The web recommendation process comprises of two parts in particular, online and off-line, regarding web server action [4]. The meta-web indexes can run a user question over various segments of web crawlers simultaneously, recover the produced results, and store up them. The advantages of meta-web search tools against the web engines are striking [5]. However, the IoT is not only about connectivity, it is about the pervasive collection and sharing of data towards a common goal [30]. Web administrations, for example, email, document transformation, and word processing are given as Software-as-a-Service (SaaS) through different [6] cloud specialist organizations. Platform-as-a-Service (PaaS) administrations offer help in building and conveying web applications and web-based administrations. Infrastructure-as-a-Service (IaaS) provides processing framework including virtual machines, PC equipment, and database as administration [7].

A novel ontological way is presented here to deal with user profiling inside recommender systems [8]. Another approach to suggest items is based on the appraisals given by other individuals who loved the item before [9]. Communitarian recommender frameworks execute this by requesting those individuals' rate items expressively and afterward suggest new things that comparative users evaluated exceedingly [10]. The user profiling approach which is utilized by the most recommender frameworks is behavior-based, usually utilizing a double class model to indicate what users find fascinating and interesting [11]. So, the proposed procedure advances an E-learning framework by M-tree chain of command, which is controlled by an ontology for a semantic relationship using fuzzy logic in IoT [12].

The method of taking decisions according to the fuzzy logic classification is used. M-tree creation frames tree in light of semantic relations [13]. Rather than taking user rating, this study attempts at discovering similitudes among the articles utilizing fuzzy membership capacities and induction rules [14]. The fuzzy set techniques are utilized for the resulting development of justifications and rules. Hybrid frameworks that endeavor to consolidate the upsides of clustering recommender frameworks have demonstrated mainstream to-date [15].The potential chance in big data processing and examination in the IoT and feature the part of information investigation in IoT applications [35]. The contribution of the present work is WPR framework by utilizing a hybrid procedure (RFC-CSO). A user profile and ontology-based fuzzy recommendation motor are provided with a broad observational correlation of various fuzzy information membership derivations for recommendation or personalization process. For this investigation, the current study considered differing joins from various web search tools in an e-commerce application, improving the positioning of recommendation framework and producing rules that are advanced in machine learning RFC in IoT.

The rest of this paper is organized as follows: In section 2, the recommendation system papers are reviewed. Section 3 presents the purpose of the current proposed model. An elaborate explanation of the proposed model i.e., user profile generation, and ontology and hybrid technique are discussed in the section 4. Then section 5 shows the results with comparative analysis and finally the work is concluded in section 6.

2. Literature review

In 2018,Jianliang Wei *et al.* [16] proposed a strategy to decide user specialist in a social labeling framework. In this study, the quality expert and the amount expert of users were computed from a user co-event arrange, which is collected from users' support in the social labeling framework. On this premise, an asset show was built by summing up the labels from every user and their weights were compared to indicate every asset in the gathering. The user models were then retrieved in view of the asset models, and cosine closeness was utilized for making asset recommendations to users.

The adequacy of a meta-web engine is significantly controlled by the nature of the outcomes it returns, in light of user inquiries by PappuSrinivasa Rao and DevaraVasumathi in 2016 [17]. They recommended the utilization of fuzzy-bat and the purpose is to blend the score calculation module successfully. At first, an inquiry is fed into various web engines that are utilized and the best 'n' list from each internet searcher is decided so as to process additionally for that method. The framework positions and consolidations of the connections were acquired from various web indexes for the inquiry that was fed.

A cloud service recommendation framework based upon semantic innovations was investigated by

SaravanaBalaji *et al.* in 2016 [18]. This framework analyzes the cloud benefit portrayal archives with the help of a natural language processing method; the essential idea of the cloud benefit was distinguished and the fuzzy administration ontology clusters were then refreshed. The user question was prepared to utilize language processing methods and fuzzy connectives were utilized to refine the inquiry in light of first-arrange horn statement rationale and Disjunctive Normal Form (DNF).

Ramesh *et al.* conducted a study in 2016 [19] to fuse semantics learning in every one of the periods of web usage mining process. CloSpan, a best-in-class calculation for sequential pattern mining is connected over the semantic space to create visited sequential patterns. The created, semantically-enhanced examples were encouraged to WPR display in the offline stage. The test comes about indicated are promising and demonstrated a huge change in the nature of the recommendations.

In 2017,XianbingMeng *et al.* [20] proposed mimicking the hierarchal request in the chicken swarm and the behaviors of the chicken swarm including chickens, hens, and chicks. CSO could productively separate the chickens' swarm knowledge to optimize issues. The twelve benchmark issues and a speed reducer configuration were examined and directed to contrast the execution of CSO and that of different calculations.

The Internet of Things (IoT) is overpopulated by a huge number of objects along with millions of interactions and services. It recommended then the SIoT is that each question in the IoT can utilize its companions' or friends-of-friends' connections to look for a particular administration. The issue of link determination of companions and scrutinizes five techniques in the literature in by Wail Mardini *et al.* [28].

3. Motivation for Study

Nowadays since a product recommendation engine mainly runs on data, a company may not have the storage capacity to store enormous amount of data from visitors on site. Many a times, customers tend to take a look at their item recommendation from their last perusing predominantly because they discover a better chance for good items. The development of this model is semi-robotized with the goal that endeavors of designers can be diminished. The use of domain knowledge can offer tremendous advantages in IoT systems [32]. Recommendations from friends and family are often considered because their opinions add value and trust in electronic-commerce sites in IoT. They recognize what we like superior to any other individual. This is the sole reason they are good at recommending things and is what recommendation systems attempt to model. Depending on the motivations behind ontologies, they can be designed as domain conceptualizations of various degrees of custom and can be in the form of concept schemes, taxonomies, conceptual data models, or general logical theories.

4. Methodology for Proposed Web Page Recommendation Analysis

WPR plays a critical part in intelligent web systems. Its valuable knowledge discovery from web utilization data and acceptable information portrayal for compelling web page recommendations are essential and tricky [31]. In this work, an e-commerce website is recommended using innovative methodology. Initially the web pages are to be collected through the internet in search engine. The first step is to preprocess the collected web pages i.e., cleaning process to remove illegible links in internet. Recommendation process system is based on user knowledge in learning phase and the advantage of this knowledge is to create the ontology for searching and user-friendly purpose. The user profile contains only those web pages (IoT) that passed certain confidence support and weights values. It considers both semantic and clustering similarities between learners in knowledge structures. Moreover, a set of similar page items have clustered through hybrid method considered i.e., RFC gets combined with CSO algorithm, the contribution of optimization in this clustering as adjust few parameters in a cluster model [33-38]. Finally, in the recommendation process, the ratings are smoothed among all clusters to predict the ignored data and make a recommendation. This proposed WPR system follows the important steps given below.

– Collect web page data
– Data cleaning model
– User profile generation (Learner Phase)
– A cluster of similar data
– Recommendation system

4.1. Knowledge extraction from weblog

A few users utilize meta-web search tools directly or indirectly to access and assemble data in excess from one data source. Knowledge discovery and data mining involves impressive significance. Given the ongoing development in the field, it is not astounding that wide assortments of strategies are currently accessible to researchers. A learning module comprises of substance substances with a supplementary way to progress through the business items in IoT. The learning substance module contains each user's access record that has the information such as customer's IP address, ask for time, requested URL, user ID, HTTP status code, and so forth.

4.2. Data cleaning

Pre-processing is required to trade the data into relevant shape for pattern finding. Normally, raw web log data is boisterous and immaterial. For evacuating unpredictable data preprocessing, the current study identified the distinctive user session from generally exceptional and poor information that can be accessed in log records. The cleaned and filtered [21] weblog document is passed to ontology-based weblog parser. All the ontology occurrences indicated by the web pages are separated by changing over the weblog to a succession of semantic items.

4.3. User profile generation

A user profile model is contrived with the aim of loaning some assistance to the user by trusting him as a student. Each web-page has a title which contains keywords that grasp the semantics of the web-page and in view of these certainties to find the space information from the titles of the visited web-pages. For most of the part, user profile generation process is in two different ways i.e., intrigue and intension-based modeling. In the current study, E-trade shopping websites join and the ontology-based user profile were considered as illustrated in figure 1.

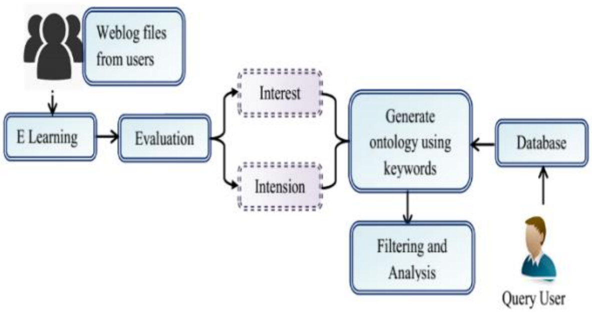

Fig. 1. User profile-based ontology model.

4.3.1. Interest modeling

A user may remember a few interests and each intrigue has lots of items identified with it in the framework. In this way, one interest might be portrayed differently by various users, while diverse interests might be depicted as something. A function is required to register the interest level of the user regarding new items, models, cost and so forth.

4.3.2. Intension modeling

The user model-proposed gauges the user expectation amid the discourse i.e., the information that the user provides during the dialogue with a specific end goal to accomplish their target. For example, for the user action that compares to passing the birthplace of an excursion, the subtask might be timetable inquiry; the named substance could be the name of the behaviour.

4.4. Learning phase

A learning module comprises of content items with an accompanying path for progressing through the items. The learning contents module contains basic learning materials such as connection, content, image and so on. This list contains the extracted space idea from virtual document entered by the user [22]. Log record is a document that lists the activities which happened. With log document investigation, one can conceive a smart thought of where guests are coming in the structure, how regularly they return and how they explore a site. In this work, the learning procedure can be considered as a clustering framework that requires no domain information and generally do not gather complex user behavior. The ontology (keywords) and this clustering model are examined in the following segment.

4.4.1. Ontology for web log data

A few libraries' information is gathered and the required information for creating ontology is separated as classes, people, and properties. Ontologies-based web mining can be utilized to enhance search the web data by including ontology explanations, better browsing capacities and personalization of web data from the client's profile which has been illustrated as model in figure 2.

From this figure, it is understood that the ontology structure is made for WPR process. The technique characterizes an ontology network rather than independent ontologies and just interconnect the ontologies in the presence of meta-connections among

the considered ontologies. Web service advancement situations bring such adaptability and straightforwardness. The ontology should support the improvement of apparatuses, which empower continuous basic leadership for hybrid clustering process.

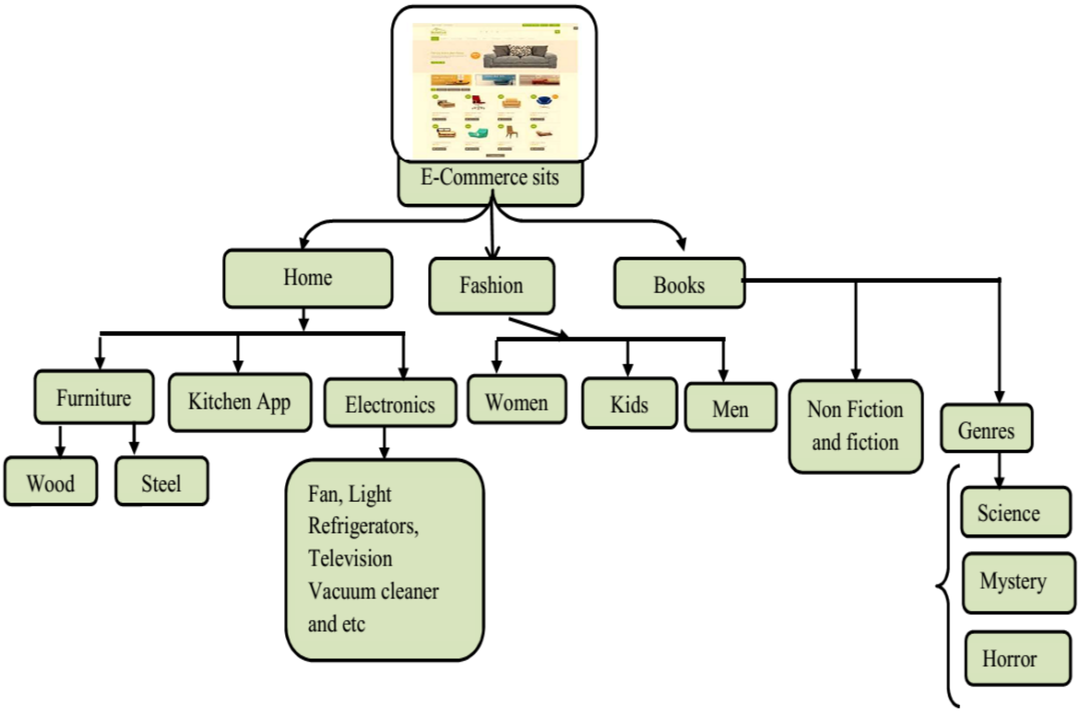

Fig 2: Ontology structure for the proposed work.

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4.5. Hybrid clustering phase (RFC- CSO)

The proposed RFC includes the ideas of fuzzy memberships, both probabilistic and plausibility, of fuzzy sets, as well as lower and upper approximations of rough sets into the C-Means process. While a combination of both probabilistic and plausibility memberships of fuzzy sets empowers proficient treatment of overlapping groups in noisy condition, the rough sets manage vulnerability, vagueness, and deficiency in cluster definition. This clustering model consolidates both Fuzzy C-Means and Rough set hypothesis.

4.5.1. Fuzzy C-Means (FCM)

Fuzzy C-Means clustering is an iterative system. To begin with, the starting fuzzy partition network is made and introductory fuzzy cluster centers are evaluated. In each movement of the iteration, the cluster centers and the membership grade points are re-designed and the objective function is minimized to find the best domain for the clusters.

Rough sets: The rough set hypothesis is yet another way to deal vagueness. Corresponding to the fuzzy set hypothesis, it is the traditional set hypothesis or however it is inserted in it. The rough set hypothesis can be seen as a particular usage of thought vagueness, i.e., imprecision in this approach is communicated by a boundary area of a set, and not by a fractional membership, as in fuzzy set hypothesis.

4.5.2. Proposed clustering for similar data

In such an ontology system, a group called outlier is built. The outlier comprises of concepts that do not have place with any of the distinguished clusters. The outlier would frame the non-taxonomic relation and different clusters shape the scientific categorization connection among the concepts. For the evaluation of distance between the concepts, Minkowski distance measure is used. The similarity distances between every one of the concepts are figured. Every one of the concepts is then plotted in a space and each space is isolated by their respective distance. For fuzzy group formation, the distance between [23] the concept and the central concept of a cluster must be recognized. This similarity data clustering process functions as in the steps discussed below.

Objective function: The proposed RFC is partitioned into clusters by minimizing objective equation (1).

Membership function: For solving objective condition, the membership function is analyzed as shown in the equation (2).

Similarity Evaluation: Minkowski distance is generally called the summed-up distance metric. According to the condition 3 given below, it is to be observed that when m=2, the distance transforms into Euclidean distance. This distance metric is a variety of Minkowski distance metric, where m=∞ (taking a state of repression).

Rule generation: The rules are effectively developed once the 'reduce' has been figured by overlying the 'diminish' over the starting decision and reading of the value. This investigates ontology-based start data which is utilized for the rule generation process. For example, the input is considered as R1, R2, and R3 and its range from [0, 5] and the output cluster is taken as C1, C2, C3, and C4. This investigation utilized 'AND' and 'OR' work for input to group the data.

Mathematical Model for Optimal RFC clustering

$$O_b(M,N) = \sum_{j=1}^{n}\sum_{i=1}^{k} \alpha_{ij}^{b} dis^2 \tag{1}$$

$$\alpha_{ij} = 1 \Big/ \sum_{i=1}^{k} \left(dis_{ij}^2 \Big/ dis_{ij}^2 \right)^{1/b-1} \tag{2}$$

$$Dis = \left(\sum_{k=1}^{d} \left| R1_{ik} - R2_{jk} \right|^{\frac{1}{m}} \right)^{b} \tag{3}$$

Centroid:

$$Cen = \sum_{j=1}^{n} \alpha_{ij}^{b} R_j \Big/ \sum_{j=1}^{n} \alpha_{ij}^{b} \tag{4}$$

Example rules

If R1=4 AND R2=3.5 OR R3= 2 then cluster as C1
If R1=2 AND R3=3.5 then cluster as C2
If R2=3 AND R3= 0.8 then cluster as C1
If R1=1.69 then cluster as C3
If R3=2.4 then cluster as C3
If R2=3.9 AND R1=4 then cluster as C2

In the above equations, the representation $O_b(M,N)$ is an objective function, b, i *and* k are Fuzziness Indices, $b \in [1, \infty]$, cen is a centroid and dis as the minimum distance calculation. The rough set theory creates the set of rules in this way. If the set of rule is created, next the rule endures the optimization process.

4.5.3. Rule optimization: Chicken Swarm Optimization (CSO)

CSO is a stochastic optimization strategy and its working principle is based on searching the behavior of chicken swarm which recreates the hierarchy order and behaviours' in a chicken swarm. This enhancement method has three different groups for optimizing the rules.

- In the chicken swarm, there exist a few groups. Each gathering contains a dominant rooster chicken, a few hens, and chicks.
- The chickens, with best fitness values, would be out of the herd as chickens and every one of which would be the head chicken in a gathering [24]. The chickens with most exceeding bad fitness value would be assigned as chicks whereas others would be the hens. The hens haphazardly pick which group to live in.
- Hierarchal order, dominance relationship and mother-kid relationship in a gathering stay unchanged in light of this solution with updated new groups.
- Chickens follow their group-mate chicken to search of food, while they may prevent the other ones from eating their own particular food. Expert chickens would arbitrarily take away the great food that was effectively found by others.
- The chicks search for food around their mom whereas the prevailing chicks have an advantage in the rivalry for food.

Steps:

Initialization: In the initialization step, rules were generated for CSO problem with the help of fitness solution set divided into three groups such as

$Group1: R_N$ Number of Roosters

$Group\,2: H_N$ Number of Hens

$Group\,3: C_N$ Number of chickens

$Group\,4: M_N$ Number of Mother hens

These all group solutions are represented as $R_{i,j}^{t} \Rightarrow (i \in (1,...N))$. Thus the best RN chickens correspond to the ones with RN minimal fitness values.

Fitness evaluation: With the help of initializing rule solution, the fitness function is evaluated and is shown in the equation (1) with its minimal function.

Updating new rules (Movement of each group): The chickens, with fitness values, have a need for food access than the ones with more regrettable fitness. For effortlessness, this case can be reenacted by the circumstance, that the chickens with 'better fitness values' can scan for food in more extensive scope of spots, than that of the chickens with 'worst fitness values'. This scenario is depicted as follows

$$R_{i,j}^{t+1} = R_{i,j}^{t} * (1 + Rand\,(0, \lambda^2)) \tag{5}$$

$$\lambda^2 = \begin{cases} 1 & if \;\; f_i \le f_k \\ \exp\left(f_k - f_i \big/ |\, f_i \,| + \varepsilon \right), other\,wise & k \in [1, N], k \ne i \end{cases} \tag{6}$$

This rule optimization model as given the above equation (6), where the parameters are $(Rand\,(0, \lambda^2)$ denoting to be a Gaussian distribution with mean 0 and standard deviation λ^2 . ε is used to avoid zero-division-error is the smallest constant in the computer, k a rooster's index is randomly selected from the rooster's group and f is the fitness value of the corresponding R .

Dominance relation model: With respect to hens, they can follow their gathering mate chickens to scan for food. In addition, they would arbitrarily steal the good food found by different chickens. However they would be subdued by alternate chickens. The more predominant hens would have an advantage in competing for food than the more compliant ones.

$$R_{i,j}^{t+1} = R_{i,j}^{t} + K1 * Rand * (R_{r1,j}^{t} - (R_{i,j}^{t}) + K2 * Rand * (R_{r2,j}^{t} - (R_{i,j}^{t}) \tag{7}$$

$$K1 = \exp\left((f_i - f_{fr1}) / (abs(f_i) + \varepsilon) \right) \qquad and \qquad K2 = \exp\left((f_{r2} - - f_i) \right) \tag{8}$$

where $Rand$ is a uniform random number and an index of the rooster, which is the ith hen's group-mate and $r2 \in [1...N]$ is an index of the chicken (rooster or hen) randomly chosen from the swarm $r1 \ne r2$. The bigger the difference between the two chickens' fitness values are, the smaller S2 and the bigger the gap between the two chickens' positions will be. Thus the hens would not easily steal the food found by other chickens. The chicks move around their mother to forage for food which is described as follows

$$R_{i,j}^{t+1} = R_{i,j}^{t} + uo * (R_{m,j}^{t} - R_{i,j}^{t}) \tag{9}$$

where $R_{i,j}^{t}$ stands for the position of the ith chick's mother and $uo \in (0,2)$ is a parameter, which means that the chick would follow its mother to forage for food.

4.5.4. Optimal rules for RFC

The testing data with the diminished attribute is determined to fuzzy logic framework, where the test data is changed to fuzzified-value based on its membership function. Next, in view of the membership function, the fuzzified-input is coordinated with the fuzzy rules as characterized in the optimal rule base.

4.6. Recommendation model

RFC methodology decides based on optimal fuzzy rules and known realities. Then summed up Modus Ponens is a speculation of modus-ponens which is the basic rule of surmising in conventional two-valued logic. The proposed approach gives a reasonable opportunity to the recently-added thing to be incorporated into the recommendation list of the client's objective within some undefined time frame. Expound perspective of the proposed model is demonstrated in the figure 3. The items are placed in recommendation list of the objective user in decreasing order of their last recommendation estimations of URL web-based business website. In this procedure, if another user comes, there is a need to make a few inquiries to them and based on their appropriate response; some website can be proposed to them which rely upon the user profile recommendation process.

5. Analysis of Results

The proposed recommendation model was implemented in Java programming language with JDK 1.7 for an i5processor, 1.6GHz, and 8GB RAM. This section discusses the performance results for the proposed WPR and existing models with database description.

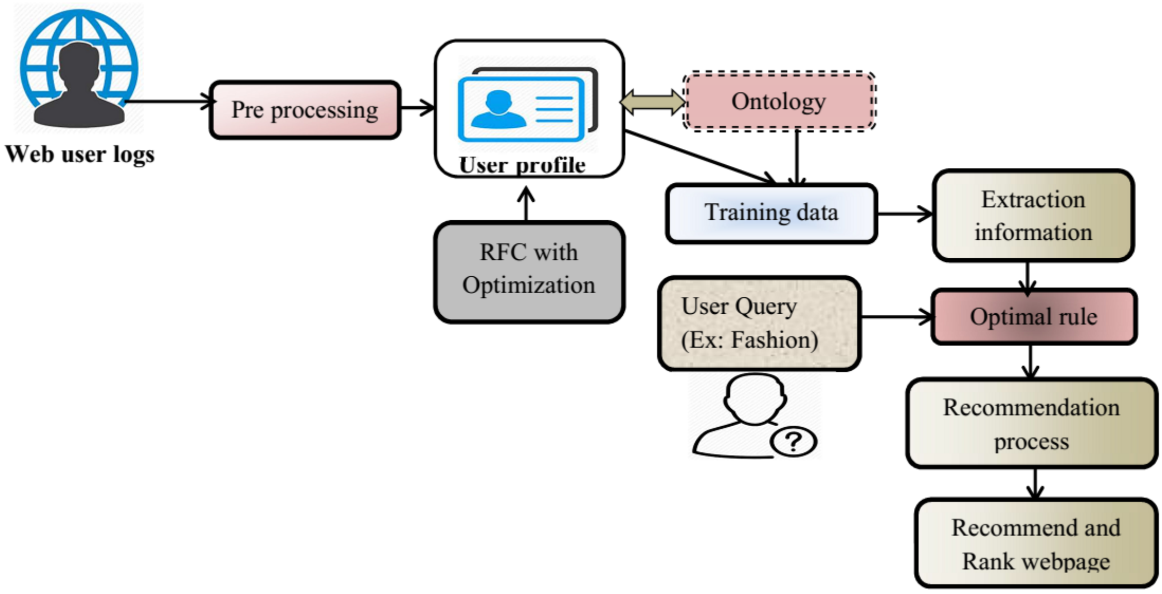


Fig 3: Diagram for optimal fuzzy-based WPR system.

The millions of WWW link collected from the different engine for various E commence sites Like Amazon from internet, sample products links are shown in table 1 and its collected from UCI machine respiratory library [25-27].

Table1: Sampler Database model for WPR

https://www.amazon.in/TVs/b/ref=sd_allcat_sbc_tvelec_television?ie=UTF8&node=1389396031%20Appliances_0_Televisions&otracker=nmenu_sub_TVs%20and%20Appliances_0_Television
https://www.amazon.in/Suitcases/b/ref=sd_allcat_sbc_sportslugg_checkinbags?ie=UTF8&node=2917450031
https://www.amazon.in/Goldmedal-Curve-205101-Plastic-iStrip/dp/B0114BF6C0/ref=sr_1_1?s=kitchen&ie=UTF8&qid=1534903807&sr=1-1
https://www.amazon.in/gp/site-directory?ref=nav_shopall_btn
http://speed-open2.com/rtb/s/AH7GfFusNQAA1KYBAElOFwASAMLzbRwA
https://www.amazon.in/TVs/b/ref=sd_allcat_sbc_tvelec_television?ie=UTF8&node=1389396031

5.1. Analysis measures

Precision

$$Pre = \frac{No.of\ \ Applicable\ Service \cap Numberof\ Recovered\ Service}{Total\ \ No.of\ Recovered\ Service} \tag{10}$$

Recall

$$Recall = \frac{No.of\ \ Applicable\ Service \cap No.of\ Recovered\ Service}{Total\ \ No.of\ \ Applicable\ Service} \tag{11}$$

F measure

$$F = \frac{2(Pre * Recall)}{Pre + Recall} \tag{12}$$

Table 2: Top list of E commerce based on User profiles

S.No.	Links	Number of users- ranking				Final Ranking
		3	6	9	12	
1	https://www.amazon.in/Suitcases/b/ref=sd_allcat_sbc_sportslugg_checkinbags?ie=UTF8&node=2917450031	-	-	6	7	6
2	https://www.amazon.in/TVs/b/ref=sd_allcat_sbc_tvelec_television?ie=UTF8&node=1389396031	2	3	5	4	8
3	https://www.amazon.in/Refrigerators/b/ref=sd_allcat_sbc_tvelec_fridges?ie=UTF8&node=1380365031	8	7	8	10	1
4	https://www.amazon.in/gp/site-directory?ref=nav_shopall_btn	2	1	-	-	10
5	https://www.amazon.in/Goldmedal-Curve-205101-Plastic-i-Strip/dp/B0114BF6C0/ref=sr_1_1?s=kitchen&ie=UTF8&qid=1534903807&sr=1-1	6	7	10	8	3
6	https://www.amazon.in/Kitchen-Storage-Containers/b/ref=nav_shopall_sbc_hk_kitchenstorage?ie=UTF8&node=1379989031	5	6	6	7	4
7	https://www.amazon.in/mobile-phones/b/ref=sd_allcat_sbc_mobcomp_all_mobiles?ie=UTF8&node=1389401031	4	7	9	8	2
8	https://www.amazon.in/b/?_encoding=UTF8&node=1380441031&ref_=sv_top_hk_mega_3	-	-	7	4	7
9	https://www.amazon.in/b/?_encoding=UTF8&node=4286640031&ref_=sv_top_hk_mega_6	2	-	-	5	9
10	https://www.amazon.in/beauty/b/ref=sd_allcat_sbc_bhg_beauty_all?ie=UTF8&node=1355016031	6	2	4	9	5

The adequacy of the proposed WPR and ranking procedure is appeared in table 2. Here the distinctive users were considered with various online business locales, according to the proposed system in which the rank was allotted to every user who were then finally ranked and showed the best website to shop in view of the class. In the end, the positioned lists of the 15 users got changed over to a single-positioned list to play out the assessment of the current proposed method.

Table 3: Similarity measure Vs Optimal clusters

Number of optimal clusters	Similarity- Minkowshi	Similarity- Euclidean
2	0.58	0.85
4	0.62	0.65
6	0.56	0.78
8	0.44	0.59
10	0.49	0.66
12	0.56	0.61

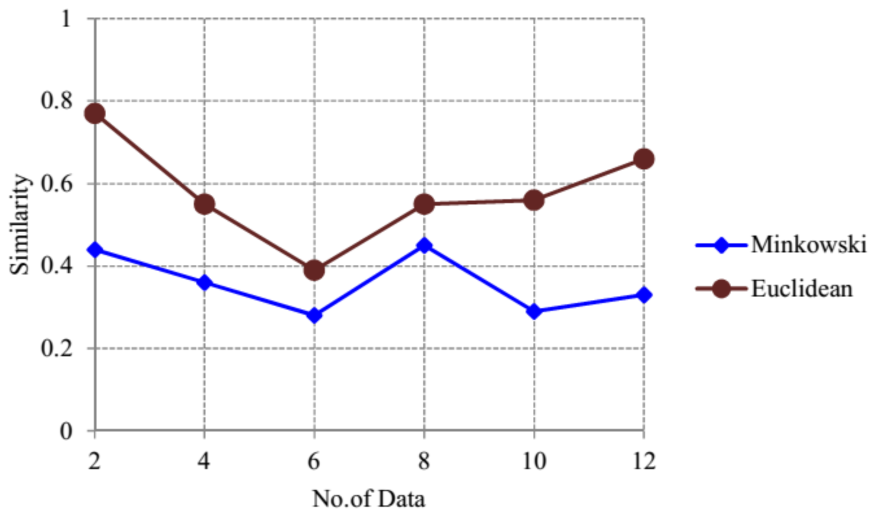


Fig 4: Number Data Vs Similarity

Table 3 and Figure 4 demonstrate the similarity measure investigation versus the users and number of data. The examination of Minkowski and Euclidean similarity measures for the clusters was created utilizing RFC with the optimization process. It is unmistakably portrayed that Euclidean comparability value is higher than the min. similarity value. This is a direct result of the binary portrayal of the web data. This various-leveled clustering calculation, though basic, will neither revokes the union activities performed already nor performs question swapping between groups which may prompt low-quality clusters and users. From both table and the chart, the least similarity i.e., 0.54 in Minkowski measure is differed with another one.

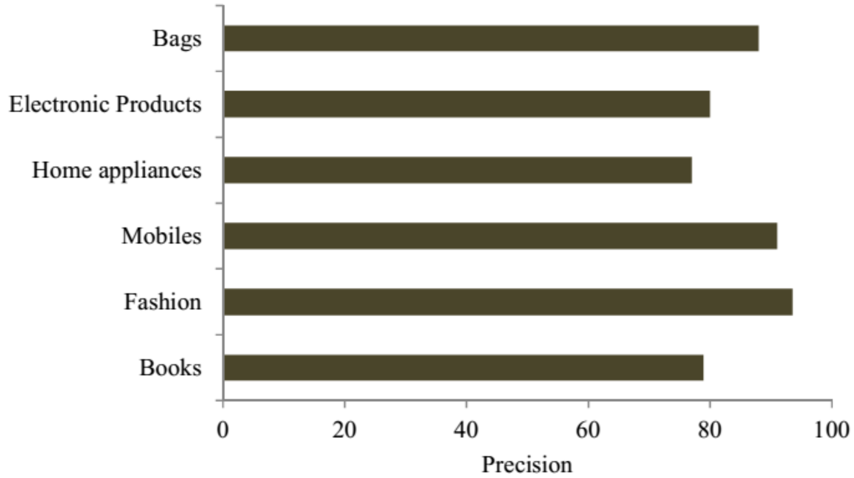


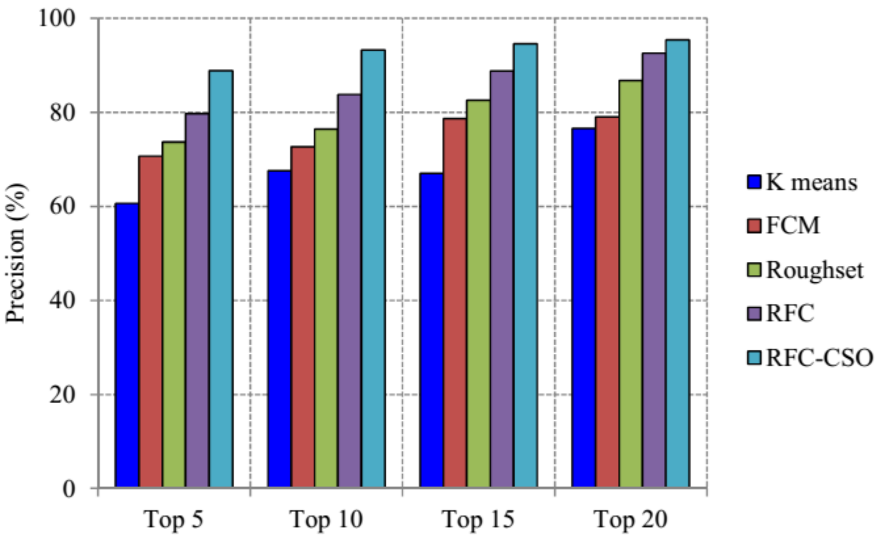
Fig 5: Query word Vs Performance

Diverse shopping things are classified in light of the user prerequisites and for this examination ontology structure, a graphical portrayal as appeared in the figure 5 is made. The precision measure is characterized as a degree to which the inescapable browsing pattern is caught as proposed by the framework matches with the real browsing pattern of the user. Most users would prefer not to set aside the opportunity to make ontology, particularly the ones that exclusively contains concepts. Only the main ten mapped pages were kept for any concept in the individual ontology and the proposed user profile-based ontology process delivers the most extreme accuracy i.e., 89.56% of question word.

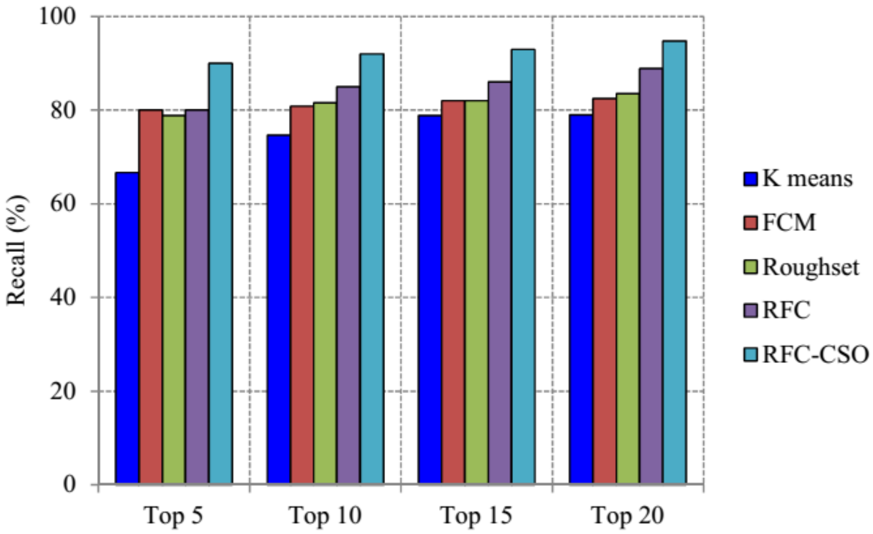
Table 4: Performance analysis for the proposed WPR (RFC-CSO)

Number of Recommendation Users	Precision	Recall	F Measure
5	84.56	86.66	86.45
10	82.15	79	82.12
15	92.12	82.12	79.45
20	91.28	76.48	92.22
25	89.28	84.56	93.22
30	93.45	89.56	91.22

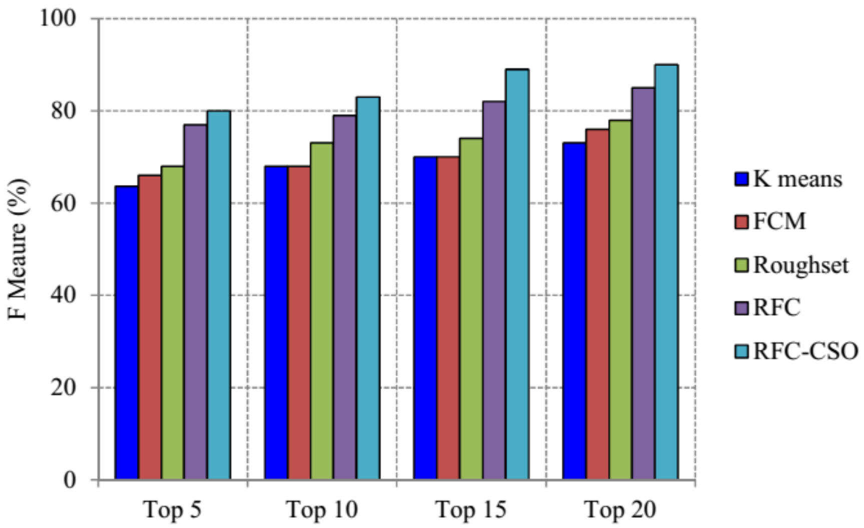
WPR process the performance measures precision, recall and F-measure based on different users as shown in the table 4. For five users, the execution values are 84.56%, 86.66%, and 86.45% and if shifting number of users, the execution got additionally changed. To accomplish the personalized web pages, this examination proposed a recommendation framework with two distinct methodologies according to the user behavior arranged by utilizing the weblog documents. The most extreme performance is 93.22% (F measure) in 25 users. Precision is the framework's capacity to produce precise recommendations and at the end of the day, the precision of the framework is dictated by the proportional value of ‘true recommendations’ to ‘all recommendations’



a) Precision



b) Recall



(c) F-Measure

Fig 6: Comparative Analysis

Figure 6 demonstrates the comparative analysis of the measures such as precision, recall and F measure for various systems such as K-means Clustering, Fuzzy C-means, rough set, RFC, and RFC-CSO (Proposed technique). Figure 6(a) demonstrates the precision rate for top N-prescribe pages which have most extreme precision as 96.56% in the current proposed technique compared to other techniques. These values are utilized to produce last recommendations for various users in the test data. The precision, recall and F-measure examination diagrams of user-based collective recommendations for the objective user are produced from all neighbors with similarity which is more prominent than or equivalent to the recommendation pages. Other measures such as 6(b) and 6(c) likewise demonstrate the maximum performance in the proposed technique compared to existing strategies i.e., the distinction is 8 to 10%. If varying the recommended pages, the execution gets additionally changed. For sure, the recommendations depend on the item preferences of the clients.

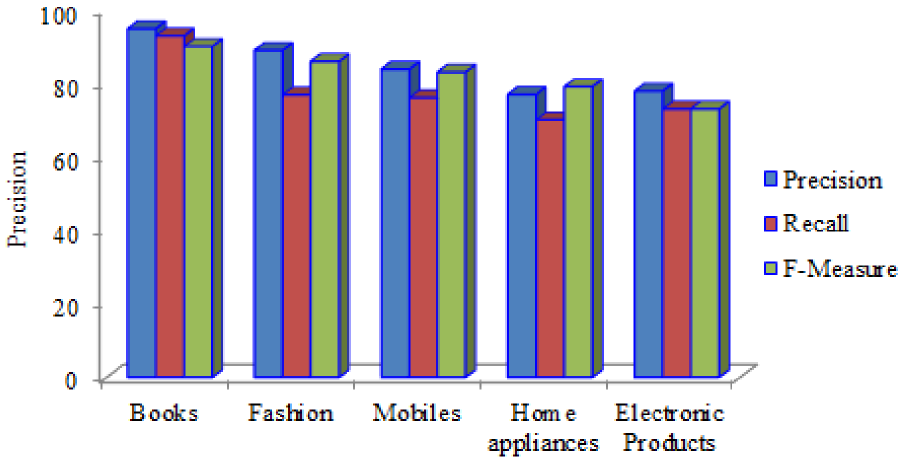


Fig 7: E commerce Site Vs performance

Figure 7 demonstrates all measurements in various locales that are books, mobiles and so on from this investigation Amazon as the most extreme precision rate 96.45% compared with others. Because of the examination, the data was collected in the form of keywords relating to the activities performed by every member. To decide the optimal number of clusters, the impacts of data division were investigated. In light of this match, the present customer is pre-classified and the limited time items are shown in a frame, worthy to the solid customer group.

6. Conclusion

Mostly, the existing e-commerce recommendation in IoT systems apply their efforts in augmenting all the interesting items of target customer to their list. In the proposed method (RFC-CSO), in recommendation list, the items are posed in such a way that those items of user's profile with ontology model begin with the recommendation procedure. This model examined the performance for the above segment for which the values of the precision, recall and F measure rate are 96.55%, 92.22% and 93.5% with better similitude measures. The proposed optimal RFC, on data related to item information, evaluations and surveys, are accessible for most of the parts in all web-based business websites in IoT. It can be effortlessly consolidated in any web-based business websites without putting many endeavors. The computed values with user-ranked list are given to the fuzzy to rank the list and the hybrid recommendations are provided, by making use of cooperative filtering which is controlled by recommendation process. In future, it can be reached out by including a tag of various items along with a web search engine in IoT with different profiles while at the same time producing recommendations.

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