

An Improved Mechanism for User Profile Generation Using Case-Based Reasoning and Weighted Association Rule Mining

Aiswarya Jayaprakash^{1*}, Bhavithra Janakiraman²

^{1,2}Department of Computer Science and Engineering, Dr.Mahalingam College of Engineering & Technology, Pollachi, Tamil Nadu 642003, India

**Corresponding Author: aiswarya@drmcet.ac.in Tel.:09095486807*

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Abstract— Web page recommender systems play a major role in web searches by retrieving most relevant results. The goal of personalized recommendation is to tailor the search results to a particular user based on his/her interest. Traditional retrieval systems are not adaptive enough to satisfy the user's individual needs and interests. A collaborative filtering approach, called Normal Recovery Collaborative Filtering (NRCF) is used to increase the accuracy of webpage recommendation. As an enhancement, this work applies Case Based Reasoning (CBR) in web searches to optimize the retrieval strategy and Weighted Association Rule Mining (WARM) algorithm to predict more accurate webpages using association rules generated specifically for individual user profiles. For any active user, the system retrieves most similar user profiles matching the current user. Weighted rules are generated based on the frequency of visit and duration spent on the page. WARM is based on the profile similarity between the active user and the computed weighted rules. Based on these rules, new pages that visited by similar users are recommended to the active user. Experiment results show that the proposed algorithm combining CBR and WARM outperforms well with more accuracy by providing more efficient and appropriate recommendation.

Keywords— Normal Recovery Collaborative Filtering, Case Based Reasoning (CBR), Weighted Association Rule Mining (WARM), Hypertext Induced Topic Search (HITS)

I. INTRODUCTION

Most of the people use webs to search and buy products as most of the products are available at cheap deals and better prices and products are from different manufacturers without any intermediate person involved. In the current era, online users are abundant with high expectations from search engines to satisfy their query with most appropriate web pages. Based on their search on web, query results must be customized to provide user satisfaction. Recommender systems is the thriving research area today, in which personalization is done to analyze user's search interest and provide better results even for those users who do not reveal their search interest explicitly. Collaborative filtering approach provides recommendations based on other users who have similar interest and preferences. These users with similar interest are called as neighbors. In this work, Collaborative filtering approach is enhanced by further filtering the neighbours and analyze users those who are very closely related using Case Based Reasoning (CBR). CBR retrieval strategy makes use of existing user profiles to map the current users' interest based on similarity knowledge. Weighted Association Rule Mining (WARM) is also applied along with CBR to further enhance the accuracy of the system.

Weighted Association Rule Mining is similar to traditional association rule mining, where weight is considered as an add-on parameter [1]. Web Mining is categorized into three different types as explained in [2]. This research is based on analysis of usage log. User profile is constructed based on URL visited by users from various IP addresses, page view and page rank. From weblog data, page view and Page Rank is computed for each user visited URL. Page view is frequency of visit to particular webpage. Page Rank is a numeric value that measure's the importance of webpage. The rest of this paper is organized as follows. In section II, related work to this paper has been discussed. Section III explains about the methodology used for recommendation in detail. In Section IV, discussed various evaluation measures and results with graph. In, Section V conclusion and future work is discussed.

II. RELATED WORK

Predictions of web pages that could likely be visited by end users are recommended based on the user interest and previous navigation history. Various traditional methods such as collaborative filtering, association rules, clustering,

sequential patterns, hybrid methods and semantic web [3] are used for such predictions. Collaborative filtering [4] is one of the most common approaches used for providing a recommendation by finding similar users. Pearson correlation coefficient and cosine based approach can be used to find similar users [5]. This traditional approach can still be improved by applying normal recovery Collaborative filtering [6]. But recommendation done using pure collaborative filtering approach may lead to problems such as popularity bias, cold start problem, handling dynamic pages etc. So, in order to provide personalized results, this paper combines Case Based Reasoning (CBR) [7] with Weighted Association Rule Mining approaches (WARM) [8]. CBR generates user profile and uses similarity knowledge to predict relevant profiles for the current active user. Such profile includes Page Rank [8] as a major feature which is computed using HITS and Page Rank algorithm. WARM is similar to traditional association rule mining and it's more efficient as it considers the importance of transactions and item sets [4].

III. METHODOLOGY

Normal Recovery Collaborative Filtering

Collaborative filtering is one of the most common approaches used. Collaborative Filtering systems collect visitor opinions on a set of objects using ratings, explicitly provided by the users or implicitly computed. In explicit ratings, users assign ratings to items or web pages, or a positive (or negative) vote to some web pages or documents [7]. The implicit ratings are computed by considering the access to a Web page. A rating matrix is constructed where each row represents a user and each column represents an item or web page keywords [9]. Items could be any type of online information resources or products in an online community such as web pages, videos, music tracks, photos, academic papers, books etc. Collaborative filtering systems predict a particular user's interest in an item using the rating matrix. Alternatively, the item-item matrix, which contains the pair-wise similarities of items, can be used as the rating matrix. Rating matrix is the basis of CF methods. The ratings collected by the system may be of both implicit and explicit forms. Although CF techniques based on implicit rating are available for a recommendation, most of the CF approaches are developed for recommending items where users can provide their preferences with explicit ratings to items.

The web log files are collected from the users' browsing history, consisting of IP address, date & time of visiting the web pages, method url/protocol, status, received byte etc. From the log file, all the web page contents are extracted, from which keywords are extracted. Page view and page rank is calculated for each url. Based on these values, user profile is constructed. The user profile is represented in matrix format. Based on user profile, user's similarity is found by applying normal recovery similarity measure [9]. Collaborative filtering approach called Normal Recovery

Collaborative Filtering (NRCF) is applied on similar users obtained, for web page recommendation. When new user enters a search query same as another similar user query, then the webpages visited by similar users are recommended to the new user

Normal recovery similarity measure is applied to the users profile and more similar users to calculate the degree of similarity between two users using (1)

$$Sim(u,v) = 1 - \frac{\sqrt{\sum_{i \in I} \left(\frac{r_{u,i} - r_{u \min}}{r_{u \max} - r_{u \min}} - \frac{r_{v,i} - r_{v \min}}{r_{v \max} - r_{v \min}} \right)^2}}{\sqrt{|I|}} \quad (1)$$

Where, i is the set of web pages that are co-visited by user u and v . $|I|$ is the number of i , i.e. total number web pages co-visited by users u and v , $r_{u,i}$ is the value of web page keyword and time spent in particular web page from user u in user web page matrix. $r_{u \min}$ and $r_{u \max}$ are the lowest and highest values of user u . $r_{v \min}$ and $r_{v \max}$ are the lowest and highest values of user v .

Some issues identified in traditional collaborative filtering system are:

- The recommender system does not provide suitable web pages to user all the time. Because the recommender system, only recommends based on similar users interest.
- Frequently visited web pages are again recommended to user. So the popular web pages are again getting popular.

Case Based Reasoning for Web Page Recommendation:

Case Based Reasoning is a process of finding solutions to new problems based on the solutions of similar past problems. In this paper, the phenomenon of such case based reasoning is applied in recommending web pages. Here, user's search profiles comprising of features such as list of keywords, page view pattern and page ranks are generated. Similar users, whose profile matches with current active user are identified using traditional collaborative filtering approach. Web log files are collected at web server based on user's browsing history. Such web log file comprises IP address of the user, date and time of access, visited uniform resource locator (URL), method of access, status and number of bytes received. From the log entries, the content of the visited URL will be extracted to analyze the keywords. Such keyword and its frequency forms user profile.

The working principle of CBR in web page recommendation is shown with an example in the following Table 1.

Table 1. Identifying Web pages to be recommended using Case Based Reasoning

Attributes	Assigned Weights	Similar Existing User 1	Similar Existing User 2	Similar Existing User 3	Similar Existing User 4	Active User (AU)
UID	NA	931	582	888	857	919
Keyword Match	0.90	0.80	0.53	0.72	0.65	Shoes
Page view	0.85	1	2	3	2	NA
Page rank	0.78	1	4	6	3	NA
Webpage Visited	NA	www.snapdeal.com	www.trendin.com	www.shoes.com	www.bata.com	?
Similarity with AU	NA	0.568	0.531	0.345	0.450	NA

From the Table 1, it is inferred that user with id 931 is most similar to active user 919. Such user profiles are compared and analysed using Weighted Association Rule Mining (WARM) approach to find more relevant web pages for further recommendation to current active user.

User Profile Generation

Page Rank

Page rank is a numerical value that measure's the webpage importance among the group of similar web pages. Such page rank is computed based on Random Surfer model [10,11]. This algorithm computes the page rank based on link structure of the web page. A page gets hold of high rank if the addition of the ranks of its backlinks is high. The rank of the given page is thus computed using (2)

$$PR(u) = (1-d) + d \sum_{v \in B(u)} \frac{PR(v)}{N_v} \quad (2)$$

Where, u represents a web page. B(u) is the set of pages that point to u. PR(u) is the page rank of page u that we want to find out. PR(v) is the page rank of page v that points to page u. N_v is the number of outgoing links of page and d is the damping factor that is set between 0 to 1. The damping factor is the decay factor that represents the chance of a user stop clicking links within a current page and then requesting another random page [8]

Page Weight

Page weight is calculated based on frequency and duration as in (3).

$$Page_{Weight} (PW) = Page_{Frequency} (PF) * Page_{Duration} (PD) \quad (3)$$

Where Page_{Duration} is total time spent by the user on a particular webpage represented by (4). A quick jump might also occur due to the short length of a web page so the size of page may affect the actual visiting time. Hence, the duration is normalized by the length of the web page, i.e. the total bytes of the page. Page_{Frequency} is the number of times that a

page is accessed by different users and it's computed using (5). A parameter that must be considered in the calculating the frequency of a page is the in-degree of that page (e.g. the number of incoming links to the page).

$$Duration(P) = \frac{TotalDuration(P)}{Size(P)} \quad (4)$$

$$\max_{q \in T} \left(\frac{TotalDuration(q)}{Size(q)} \right)$$

$$Frequency(P) = \frac{Numberofvisit(P)}{\sum_{q \in T} Numberofvisit(q)} * \frac{1}{Indegree(P)} \quad (5)$$

Keyword Similarity

Keyword similarity is found using jaccard coefficient using (6). Where A and B represents keywords.

$$jaccardsimilarity = \frac{|A \cap B|}{|A \cup B|} \quad (6)$$

Finding Similarity Score

Similarities among user profiles are calculated to identify the most similar user. The similarity between current Active User (AU) and Existing Users (EU) are computed using (7) by applying Normal Recovery Collaborative Filtering approach [9]. Based on the similarity score, neighbours of active user are identified.

$$similarity(AU, EU) = \frac{\left(\begin{array}{l} (pgview_{sim} * pgview_{weight})^+ \\ (pgrank_{sim} * pgrank_{weight})^+ \\ (keyword_{sim} * keyword_{weight})^+ \end{array} \right)}{total_{weight}} \quad (7)$$

Where, $pgview_{sim}$ is the similarity between page view calculated for any active user and existing user; $pgview_{weight}$ is the adaptive weight assigned for pageview component; $pgrank_{sim}$ is the similarity between page rank calculated for

any active user and existing user; $pgrank_{weight}$ is the weightage given for pagerank component; $keyword_{sim}$ and $keyword_{weight}$ corresponds to the similarity between keywords searched by two users and its weightage respectively. $Total_{weight}$ corresponds to the sum of weightages associated for all components.

The attributes such as page view, PageRank, keywords_similarity are assigned with weights such as 0.90, 0.85 and 0.78 respectively.

Webpage Recommendation by Applying Weighted Association Rule Mining

A weighted association rule consists of weighted items X and Y. A transaction is a set of weighted items. An item weight [4] w , where $0 \leq w \leq 1$, defines the importance of the item. 0 indicates the least important item, and 1 denotes the most important item. Weights are assigned based on visiting frequency and duration spent on a webpage. Weighted association rule [13] is in the form as in (8)

$$X \rightarrow Y \tag{8}$$

Where, X and Y are two weighted items that satisfy the following constraints: $X \subseteq I, Y \subseteq I$ and $X \cap Y = \phi$

Here, X is the body of the rule; Y is the head of the rule and I denote the item (webpage). The term ‘‘Weight’’ in WARM technique is used to show the importance of a webpage. The aim of weighted association rule mining is to steer the mining process to find significant relationships involving items with significant weights rather than exploring insignificant relationships [4]. Weighted support [8] of the association rule is determined by the percentage of transactions containing both the items X and Y, which is computed using (9)

$$WSP(X \rightarrow Y) = WSP(X \cap Y) \tag{9}$$

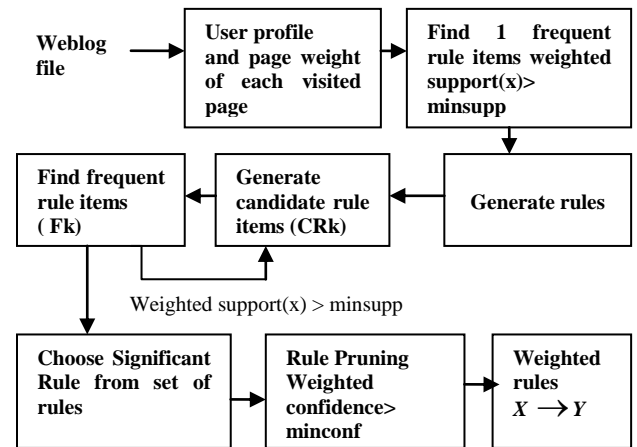
Weighted confidence [8] of association rule is the determined by the percentage of transactions containing X that also contain Y and is computed based on (10)

$$WConf(X \rightarrow Y) = \frac{WSP(X \cup Y)}{WSP(X)} \tag{10}$$

Generation of Weighted Rules

Weighted Association Rule Mining is applied to each user profile and weighted association rules are generated as per the process narrated in figure (1). Initially, one frequent item (FK-1) sets are found, whose support should be greater than minimum support value. FK-1 is then used to generate candidate item (CK) in order to find FK for $k \geq 2$. The rules with confidence value lesser than minimum confidence are

eliminated.



The rule generation process is described using the following Table 2.

Table 2. Rule Generation

Keyword	url	Pageview	pagerank
Shoes	www.bata.com	2	3
Shoes	www.snapdeal.com	1	1

The following rules are generated for weblog items in Table 2:

- $\{shoes\} \in keyword \ \& \ \{2\} \in pageview \ \& \ \{3\} \in pagerank \rightarrow \{www.bata.com\} \in webpage$
confidence: 0.85
- $\{shoes\} \in keyword \ \& \ \{1\} \in pageview \ \& \ \{1\} \in pagerank \rightarrow \{www.snapdeal.com\} \in webpage$
Confidence: 1

Similarity between User Profile & Association Rule

Current user session is represented as vector S of significance weight if user has accessed the page, otherwise $s_i = 0$. After this, match score between association rules that generated based on navigational pattern history and current active session is to be computed. The dissimilarity is calculated to measure the similarity between user and rule where S and rL represent the active user and left hand side of weighted association rule. Based on dissimilarity [13] value, a match score is computed using (11).

$$Dissimilarity(s,rL) = \sum_{i,rLi>0} \left(\frac{2*(w(S_i) - w(rLi))}{(w(S_i) + w(rLi))} \right)^2 \tag{11}$$

Match score is computed using (12),

$$Matchscore(s,rL) = 1 - \frac{1}{4} \sqrt{\frac{Dissimilarity(s,rL)}{\sum_{i,rLi>0} 1}} \tag{12}$$

As the algorithm tries to find rules that are similar to the active user session, the similarity measure between a rule and the active session is found that is dependent on the magnitude of the left-hand side of (8). Association rules might have multiple items on the right hand side of (8). But, due to the nature of the prediction problem by this approach recommendations must be independent of one another and users will select only one of several recommendations. So rules that have only singleton right-hand sides are used.

Recommendation Process

The recommendation engine is the online component of a usage-based personalization system. In order to determine which items are to be recommended, a recommendation score is computed for each page Pi. The process of computing the recommendation score is described in Figure (2).

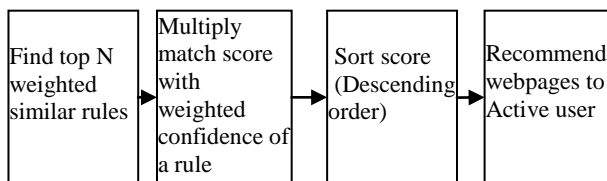


Figure 2.Calculation of Recommendation Score

Recommendation score is computed using two different factors.

They are:

1. Overall matching score of the active session to the weighted rules
2. Weighted confidence of the rule.

Given the association rule and active user S, a recommendation scores for the active session, is computed using (13)

$$Rec(s, x \Rightarrow p) = MatchScore(s, x) * wconf(x \Rightarrow p) \tag{13}$$

Match score [13] is calculated using (12) and WConf is calculated using (10). Web Page recommendation will be then based on the top web pages that has highest

recommendation score [13]. For example,

- Rec.score (s, r1) = 0.9*0.85 =0.765
- Rec.score (s, r2) = 1*1 =1

Where s represents the match score and r1, r2 represents rule 1 and rule 2 . Based on the recommendation score, webpages are sorted and then recommended in the below order

- www.snapdeal.com is recommended first
- www.bata.com is recommended second

IV. RESULTS AND DISCUSSION

A. Dataset

The weblog data is a collection of real query log data that is based on real time web users. The log file was collected from students browsing history, given by Dr.Mahalingam College of Engineering & Technology, Pollachi, Tamilnadu, India. The student details are Splitted from the log file based on IP Address and stored separately. Dataset used is of size 23,709 KB with 1 lakh entries, consists of 77 different IP addresses, date & time of visiting the web pages, method url/protocol, status, received byte, connection type etc as shown in Table 3.The extracted URLs are stored in a text file and keywords are extracted and stored in a database. Each webpage may include advertisements, pictures, videos, textual content etc. The banned and invalid urls are ignored during web content extraction. The pre-processed log will contain IP Address, date & time and url.

Table 3.Format of Log file

IP Address	Date & Time	Method URL/ Protocol	Connection type	Status	Received byte
10.1.5.210	17/Sep/2017: 07:01:16	GET http://www.google.co.in/	HTTP /1.1	200	0

1.1 Evaluation Metrics

The performance of recommender systems is evaluated using Precision, Recall, F-Measure [12] and Mean Absolute Error (MAE) [9]. Let R denote the total number of web pages in the collection, A denotes set of web pages that are answered and Ra denotes Set of relevant web pages that are retrieved. Precision is calculated using (14). It is the ratio of a number of relevant web pages retrieved to the total number of answered web pages. It is usually expressed as a percentage.

$$precision = \frac{|R_a|}{|A|} \tag{14}$$

Recall is the ratio of number of relevant web pages retrieved to the total number of web pages. It is expressed as a percentage and calculated as shown in (15).

$$\text{Recall} = \frac{|R_a|}{|R|} \tag{15}$$

F-Measure is the harmonic mean of precision and recall, the F-measure or balanced F-score is calculated using (16).

$$\text{HarmonicMean} = \frac{2}{\frac{1}{r} + \frac{1}{p}} \tag{16}$$

Mean Absolute error (MAE) is the average absolute deviations of predictions to the ground truth values. It measures the deviation of actual value and predicted value using (17).

$$\text{MAE} = \frac{\sum_{u,i} |r_{u,i} - \hat{r}_{u,i}|}{N} \tag{17}$$

Where,

- $r_{u,i}$ denotes actual accuracy of webpage i observed by the user u
- $\hat{r}_{u,i}$ denotes the predicted value of webpage i for user u
- N denotes the total number of predicted value

The current system does Personalised recommendation. For each user from different IP Address, system recommends based on their interest. In existing system, the recommendation is done based on similar user’s interest. Hence, the current system provides a personalised recommendation by suggesting only relevant web pages based on particular user’s interest. This may be proved by precision, recall, F-measure and MAE values.

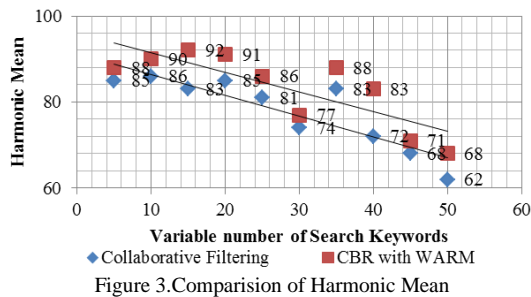


Figure 3. Comparison of Harmonic Mean

The recall, precision and F-measure were calculated for a set of keywords for performance analysis between Personalized recommendation with CBR and WARM technique and traditional Collaborative filtering technique. Implementation results show that the accuracy of recommendations based on CBR with WARM technique has been increased by 9.4%.

The detailed analysis is shown in figure 3, where the harmonic mean (F-measure) of precision and recall was analyzed for Collaborative filtering and CBR with WARM techniques. Analysis was performed in various scenarios where effective recommendations are made with multiple search keywords. The graph shows that, in all the scenarios, CBR with WARM mechanisms outperforms Collaborative filtering approach.

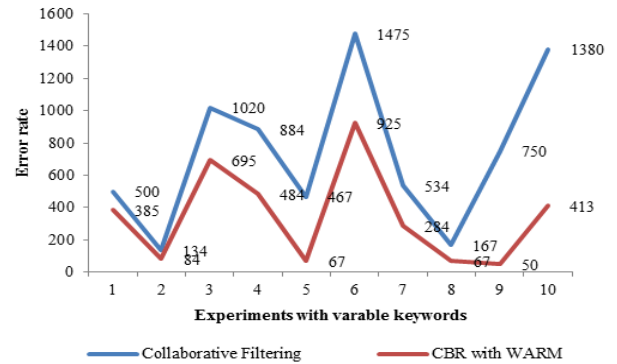


Figure 4. Analysing Mean Square Error

To detect the error rate in the proposed system, Mean Absolute Error was measured. Experiment results represent that the performance of CBR with WARM is increased with lowest error rate of 4.67% compared to collaborative filtering approach. The analysis graph is shown in figure 4.

V. CONCLUSION AND FUTURE SCOPE

In this paper, a Collaborative Filtering for webpage recommendation is discussed and an approach of CBR and WARM is proposed to improve the accuracy of recommender system. The proposed system is tested by providing single-keyword queries and the results are compared with existing collaborative filtering based recommender systems. It is observed that by using the proposed approach, the accuracy of the recommender system has been increased by 9.4% and MAE has been decreased by 4.67% compared to the Collaborative Filtering Approach. In future, this work can be further improved by providing a recommendation based on context based approaches. The proposed system can be extended to provide suggestions for hyphenated words and phrases

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Authors Profile

Ms.J.Aiswarya completed her Bachelor of Engineering from Sri Krishna College of Engineering and Technology, Coimbatore in the year 2013 and Master of Engineering from Dr.Mahalingam College of Engineering and Technology in the year 2015. She is currently working as an Assistant Professor in the Department of Computer Science and Engineering at Dr.Mahalingam College of Engineering and Technology, Pollachi, Coimbatore(D.T), Tamilnadu, India since 2015. Her research interests are Web Mining, IOT and Big data and Analytics.



J. Bhavithra completed her Bachelor of Engineering during 2003 and Master of Engineering during 2005, specialized in Computer Science and Engineering from Anna University Chennai. She is currently pursuing research under Information and Communication Engineering specialized in Web Page Recommendation systems and Machine Learning Techniques. She is currently working as Assistant Professor (Senior Scale) in the department of Computer Science and Engineering at Dr. Mahalingam College of Engineering and Technology, Pollachi, Coimbatore (DT), TamilNadu, India.

