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WEB RECOMMENDER SYSTEM BASED ON CONSUMER BEHAVIOR MODELING USING FUZZY REPRESENTATION

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Abstract *— Web surfing has become a popular activity for many consumers to make purchases online. Consumers also seek relevant information on products and services before they commit to buy. Though the World Wide Web is the biggest source of information and contains a tremendous amount of data, most of the data is irrelevant and inaccurate from users' point of view. Consequently, it has become increasingly necessary for users to utilize automated tools such as recommender systems in order to discover, extract, filter, and evaluate the desired information and resources. Web recommender systems predict the information needs of users and provide them with recommendations to facilitate their navigation. This paper proposes a Web recommender system. This system constructs a knowledge base using fuzzy temporal Web access patterns as input. Fuzzy logic is applied to requested resources of periodic pattern-based Web access activities. The fuzzy representation is used to construct a knowledge base of the user's Web access habits and behaviors. The Knowledge base is used to generate association rules which are used to provide timely personalized recommendations to the user. Experimental results on the session data of a Web site showed the effectiveness of this approach.*

Keywords*- consumer habits, personalization, recommender system, Web log mining, knowledge discovery, semantic Web, fuzzy temporal pattern.*

I. INTRODUCTION

The World Wide Web is the biggest source of information. Everyone can easily access this existing information at any time. The Web has become an increasingly popular medium for consumer to exchange or find ideas, opinions, experiences on products and services. Many consumers go further than online information sharing and actually perform purchases on the Web. The increasing availability and popularity of portable Web enabled handheld devices, looks set to fuel further growth in the volume of consumer Web traffic.

It is often hard for Web users seeking the information they really want. The problem of the user is how to divide his attention between the numerous sources of information available to him. These types of problems are described by using two new terms. The first term is "Information overload" which "refers to the state of having too much information to make a decision about a topic". The second term is "Lost in hyperspace" which describes the tendency of users to lose their way because of the nonlinear nature of browsing in a hypertext environment [1]. Consequently, it has become increasingly necessary for users to utilize automated tools in order to discover, extract, filter, and evaluate the desired information and resources. Now days it is ordinary for the Web users to come across Web sites that offer recommendations for products and services, targeted banner advertising, and individualized link selections. Web page recommender systems predict the information needs of users and provide them with recommendations to facilitate their navigation. Recommender systems are custom-built information agents that provide recommendations: suggestions for items likely to be of use to a user [2]. Recommender systems have been attracting more and more attention as a suitable approach to work against information overload and help the users of the Web information space. For example, in [3, 4, 5], the various authors described a number of personalized systems for TV program recommendations, or recommendations for multimedia channel selection. Some researchers have performed behavior profiling to further enhance the quality of the recommendations. However, it is very hard to recommend to the users as their tastes and desires are transient and fractal.

This paper focuses on effective and timely personalized Web content recommendation using consumer behavior modeling as a natural extension of the types of behavior profiling. In the present context, Personalized Web content delivery mechanisms, which take consumer habits and behaviors into consideration when preparing Web content recommendations, can be very useful in situations where the users might overlook important Web content that they simply were not aware of or not found by search engines, but nonetheless important for making a purchasing decision.

This work aims to provide consumers a Web content recommender system that generates personalized recommendations in a timely manner based on a model of their own habits and behaviors. Further, the model is stored in a knowledge base prepared in advance. This system mines periodic access patterns, and temporal information to construct the knowledge base so that subsequent applications will provide recommendations that are both useful and timely. Specifically, fuzzy logic is applied to better represent real-life temporal concepts and requested resources of periodic pattern-based Web access activities. The fuzzy representation is used to construct a knowledge base of the

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consumer's Web access habits and behaviors. This is then used to provide timely and useful personalized recommendations to the consumer.

II. RELATED WORK

This section presents a survey of work pertinent to personalized Web content recommendation and consumers' Web access pattern mining based on periodicity information. This section therefore serves to lay the foundation for further discussion of the proposed approach in Section III.

A. Web Content Recommendation Using Fuzzy Association Rule Mining

Web usage mining is the application of data mining techniques to discover usage patterns from Web data, in order to understand and better serve the needs of Web based applications. Apriori algorithm is used to generate an association rule that associates the usage pattern of the clients for a particular website. Apriori is influential algorithms for mining frequent item sets for boolean association rules [6]. Association rules can help to discover relationships between Web resources accessed by a user that would otherwise be missed, especially if the resources are disjoint. They can also be used to find groups of people with similar interests. However above Crisp Association Rule Mining (ARM) algorithms can mine only binary attributes, and require that any numerical attributes be converted to binary attributes. Until now the general method for this conversion process is to use ranges, and try to fit the values of the numerical attribute in these ranges. However, using ranges introduces uncertainty, especially at the boundaries of ranges, leading to loss of information.

A major problem of traditional association rule mining techniques is that each item in a transaction is considered only either to exist or not. Thus, the user's preference and interest on each transaction item cannot be precisely represented. Crisp association rules use sharp partitioning to transform numerical attributes to binary ones, and can potentially introduce a loss of information due to these sharp ranges.

A better way to solve this problem is to use fuzzy pattern which have attribute values represented in the interval [0, 1], instead of having just 0 and 1, and have transactions with a given attribute represented to a certain extent (in the range [0, 1]). In this way crisp binary attributes are replaced by fuzzy ones [6]. The concepts of preference and interest are fuzzy data, fuzzy logic [8] can be applied. Wong et al. [9] combine fuzzy association rule mining and case-based reasoning (CBR) [7] to improve the quality of Web access pattern prediction. Fuzzy association rules use fuzzy logic to convert numerical attributes to fuzzy attributes, thus maintaining the integrity of information conveyed by such numerical attributes. These attributes serve input to fuzzy association rules Mining Algorithm. The fuzzy rule set was found to perform better in prediction accuracy and rule coverage than traditional rule set.

B. Periodicity-Based Pattern Mining

Most of the previous work focused only on mining common sequential access patterns of Web access events, which occurred frequently within the entire duration of all Web access transactions. Methods used for the recommender system focuses on the different characteristics of the user. The fundamental requirement of an effective, personalized Web content recommendation system is to present the most relevant suggestions to the user in a timely manner. Thus, both context and temporal information are important. Currently systems tend to lack focus on temporal information. In practice, many useful sequential access patterns occur frequently only in a particular periodic time interval, such as the morning of every weekend. Discovering such periodic patterns from access log records is an important Web mining task for many applications.

Timeliness in the recommendation of relevant resources is important in many situations. For example, a user may have a tendency of reading financial news and traffic information between 9am and 10am on weekdays. Periodic association rules are rules that associate with a set of events that occur periodically. Such association rules hold only during certain time intervals, but not others. Calendar information is critical in describing the time intervals, the authors studied the problem of discovering cyclic association rules that show regular cyclic variation over time [12]. However, this work is unable to describe real-life time concepts and deal with multiple granularities of time, such as the morning of every weekend. In [13], the authors proposed calendric association rules that extend beyond cyclic association rules for handling multiple units of time. In [10], [11], Calendar schemas were proposed for discovering temporal association rules. By using calendar schema as a framework for mining temporal patterns, it requires less prior knowledge of data than the previous approaches in [12], [13].

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III. KNOWLEDGE BASE USING FUZZY PATTERN

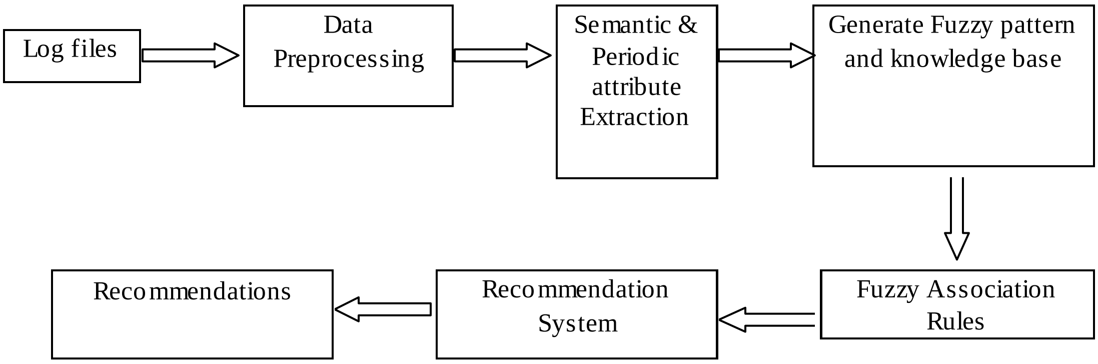

Figure 1. Block diagram of Recommendation System.

Figure 1 shows the block diagram of the proposed system.To implement, In first step Data preprocessing need to apply on web access log files. Pre-processing is the technique used to transform the raw data into a format that will be more easily and proficiently processed to do the required task. The phases of pre-processing include data cleaning, user identification and session identification. The process of data cleaning is to remove erroneous, redundant references and irrelevant data. Also, all log entries with file name suffixes such as gif, JPEG, jpeg, GIF, jpg, JPG can be eliminated since they are irrelevant. Once HTTP log files have been cleaned, the next step in the data pre-processing is the identification of users using IP address. The Session identification is a process of partition the access log of each user into distinct access sessions. If the duration of a session exceeds a certain limit, it could be considered that there is another access session of the user. Discovered from empirical findings, a 30-min threshold for the total session duration has been recommended. From this preprocessed data, it needs to extract semantic attributes and periodic patterns. Then generate Fuzzy pattern and knowledge base. Use this Fuzzy representation to generate fuzzy Association rules. These rules serve input to recommendation system to generate Recommendations.

In order to obtain meaningful results, Web usage mining must exploit the semantics of the pages visited along user paths. The URLs recorded in Web usage logs contain little semantic information about the Web content accessed by users. This makes it difficult to be used for understanding users' actual access behaviors, interests and intentions. Some form of semantic enhancement is therefore required to make the Web log data really useful. Annotate each requested URL in Web usage logs with the corresponding semantic information, i.e., One or more predefined topic, concepts or categories, such as Product News, Current Affairs, Sports and Entertainment. These attributes further referred as resource attributes which are used for the generation of fuzzy patterns.

This work deals with Web recommender that models user habits and behaviors by constructing a knowledge base using temporal Web access patterns and Web semantics as input. Using the semantic Web usage logs as inputs, it first identifies a set of periodic attributes (i.e., temporal concepts such as morning, afternoon) and a set of resource attributes (i. e., semantic information such as topic, concepts or categories) to represent periodic pattern-based Web access activities.

Fuzzy logic is applied to periodic attributes and resource attributes to represent real-life temporal concepts and requested resources of periodic pattern-based Web access activities. This representation is used to construct a knowledge base of the user's Web access habits and behaviors, which is used to provide timely personalized recommendations to the user.

If the user accesses specific resources periodically, then the user has a Web access activity (i.e., periodic Web access pattern). Use a set of periodic attributes M_p and resource attributes M_r to represent Web access activity . This proposed approach recommends to define eight real-life temporal concepts: Early Morning, Late Morning, Noon, Early Afternoon, Late Afternoon, Evening, Night and Late Night, as periodic attributes. More generally, days of the week (e.g., Monday, Tuesday, etc.) or other real-life temporal concepts (e.g. weekdays, weekends, etc.) can be also used as periodic attributes.

Using the semantic Web usage logs as inputs, it first identifies a set of periodic attributes (i.e., temporal concepts such as morning) and a set of resource attributes (i.e., useful domain ontological concepts) to represent periodic pattern-based Web access activities. A user's Web access session $S = (< URL_1, t_1 >, < URL_2, t_2 >, \dots, < URL_n, t_n >)$ is a sequence of requested URL_i with timestamp t_i $(1 \leq i \leq n)$. In general, the time spent by a user for a URL may indicate the level of interest that the user has in the content of that URL. The duration d_i of URL_i can be estimated simply as $d_i = (t_{i+1} - t_i)$. For the last requested URL URL_n in each user access session that does not have t_{n+1}, use the average duration of the current session for estimating its duration, i.e., $d_n = (d_1 + d_2 + \cdots + d_{n-1})/(n-1) = (t_n - t_1)/(n-1)$. To compute d_n, need $n > 1$, i.e., retain user access sessions that contain more than one requested URL [14]. Furthermore, evaluate the start time and end time of S as t_1 and $(t_n + d_n)$ respectively.

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A period of a user access session S is defined as a continuous time interval with a session start time $t_s(S)$ and a session end time $t_e(S)$, denoted as

$$P(S) = \begin{cases} [t_s\ (S), t_e\ (S)], & if\ t_s\ (S) \le\ t_e\ (S) \\ [0, t_e\ (S)] \cup [t_s\ (S), 24], & otherwise \end{cases} \quad (1)$$

Define a fuzzy periodic Web Usage Context K based on the preprocessed access sessions [14]. From the definition of K, we can further define the set of attributes common to user access sessions, the set of user access sessions having the same attributes, fuzzy support of a set of attributes, and the notion of Web access activity.

$$K = (G, M_p, M_r, I) \quad (2)$$

where G is a set of user access sessions and $I = R\left(G \times (M_p \cup M_r)\right)$ is a fuzzy set in the domain of $G \times (M_p \cup M_r)$ to represent fuzzy relations between access sessions $g \in$ G and attributes $m \in (M_p \cup M_r)$. Each fuzzy relation is represented by a membership value between 0 and 1.

$$\mu(g, m) = \begin{cases} \mu_p(g, m), & if\ m\ \in\ M_p \\ \mu_r(g, m), & if\ m\ \in\ M_r \end{cases}$$

From this definition, each user access session $g \in G$ can also be denoted as a fuzzy set on the domain of $M_p \cup M_r$ i.e., $g = \{m, \mu(g, m)\ |m \in (M_p \cup M_r)\}$

The membership value $\mu_p\ (g, m_p)$ for a periodic attribute $m_p \epsilon M_p$ in a user access session $g \in G$ can be computed using the period of g, i.e., $p(g)$. Here, the member function is defined as $\mu_p\ (g, m_p) = max_{t\epsilon p(g)}\{\mu_p(t, M_p)\}$, where $\mu_p(t, M_p)$ is defined in Figure 2 which is modified from [14].

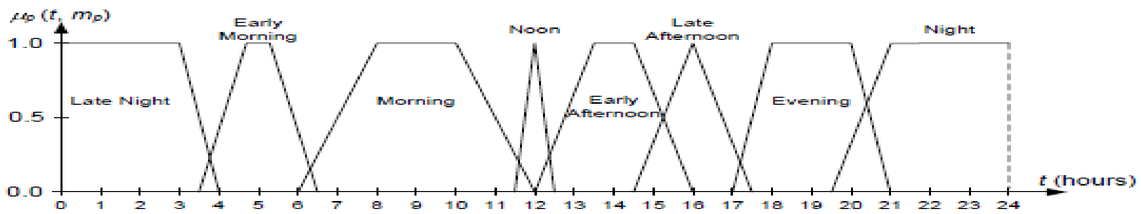

Figure 2. Member function $\mu_p(t, M_p)$

The membership value $\mu_r\ (g, m_r)$ for a resource attribute $m_r \epsilon M_r$ in a user access session $g \in G$ can be computed using the total duration of m_r i.e., $d(g, m_r)$ [14]. The membership value of the resource attribute is defined as

$$\mu_r\ (g, m_r) = \begin{cases} 0 & ,if\ z(g, m_r) < \frac{1}{2}\ Z(m_r) \\ \frac{2z(g, m_r)}{Z(m_r)} - 1\ , & if\ \frac{1}{2}\ Z(m_r) \le z(g, m_r) \le Z(m_r) \\ 1 & if\ z(g, m_r) >\ Z(m_r) \end{cases}$$

where $z(g, m_r) = \frac{d(g, m_r)}{t_s\ (g) -\ t_e\ (g)} e_r$

$$Z(m_r) = \frac{\sum_{g_k \epsilon G} d(g_k, m_r)}{\sum_{g_k \epsilon G}(t_s\ (g_k) -\ t_e\ (g_k))}$$

$Z(m_r)$ is the proportion of the total duration of accessing the resource m_r in all Web access sessions of the user, which indicates the user's global interest of the resource m_r. $z(g, m_r)$ is the proportion of the duration of accessing the resource m_r within the user access session g, weighted by an emotional influence factor $e_r = 1$.

Table 1: An Example Of Fuzzy Periodic And Resource Web Usage Context Of A User

SessionID	P1	P2	P3	R1	R2	R3
S1	0.6	0.5	0	0.8	0	0.6
S2	0	0.4	0.8	0	0	0.9
S3	0	0	1.0	0	0.7	0.5
S4	0	0.8	0.6	0.8	0.6	0.5
S5	0	0	1.0	0	0.9	0

Table 1 shows an example Web Usage Context of a user, which consists of five user access sessions, three periodic attributes "P1 (Late Afternoon)", "P2 (Evening)" and "P3 (Night)", and three resource attribute "R1 ", "R2" and "R3".

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The system then identifies the activity relationships in order to construct user behavior knowledge base [14]. Given a Web Usage Context $K = (G, M_p, M_r, I)$ the fuzzy support of a set of attributes $B \subseteq M_p \cup M_r$ and $B \neq 0$

$$Sup(B) = \frac{\sum_{g \in B}(\mu_p(g) \times \mu_r(g))}{|G|}$$

Where

$$\mu_p(g) = \begin{cases} min_{m_p \in (B \cap M_p)}\{\mu_p(g, m_p)\}, & if\ B \cap M_p \neq 0 \\ 1, & otherwise \end{cases}$$

$$\mu_r(g) = \begin{cases} min_{m_r \in (B \cap M_r)}\{\mu_r(g, m_r)\}, & if\ B \cap M_r \neq 0 \\ 1, & otherwise \end{cases}$$

Web access activity $v(B) = \{m, \mu(B, m) | m \in B\}$, where $\mu(B, m) = max_{g \in B}\{\mu(g, m)\}$. The fuzzy support of a Web access activity $v(B)$ is defined as $Sup(v(B)) = Sup(B)$ and the fuzzy confidence of v(B) is defines as $Conf(v(B)) = \frac{Sup(B)}{Sup(B \cap M_p)}$.

The next step is to construct a knowledge structure to represent all relevant activity relationships. For example, suppose there are two Web access activities for a user known as $v(B_i), v(B_j) \in W_p$ where W_p is the set of all Web access activity of a user, $v(B_i)$ is sub-activity of $v(B_j)$ if and only if $B_j \subset B_i$. Virtual Web access activity $v(\emptyset)$ represents the super-activity of all other Web access activities and therefore sits at the root of the knowledge structure with $Sup(v(\emptyset)) = 1.0$ and $Conf(v(\emptyset)) = 1.0$. Figure 3 shows Segment of user behavior knowledge base with the support and confidence of Web access activities [14].

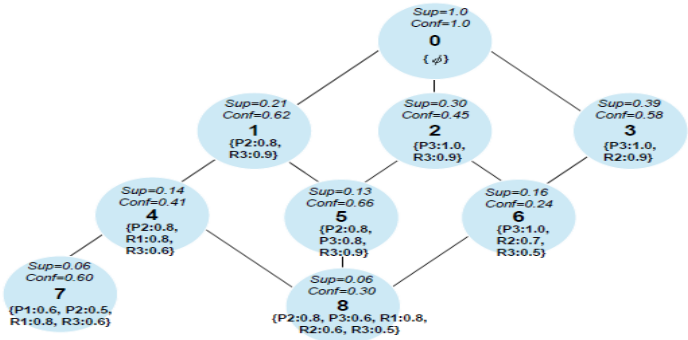

Figure 3. Segment Of User Behavior Knowledge Base

IV. RECOMMENDER SYSTEM BASED ON ASSOCIATION RULE DISCOVERY

Association rule mining is one of the most important and widespread data mining techniques. Association rules capture the relationships among items based on their patterns of co-occurrence across transactions [15]. In the Web environment, association rules are typically applied to HTTP server log data that contain historical user sessions. Web sessions can be regarded as an important source of information about users. Association rules that reveal similarities between the items derived from user behavior can be simply utilized in recommender systems. The recommendation system suggests to the current user some Web pages that appear to be useful [16].

The problem of association rule mining is defined as: Let $I = \{i_1, i_2, i_3 \ldots i_n\}$ be a set of n binary attributes called items. Let $D = \{t_1, t_2, t_3 \ldots t_m\}$ be a set of transactions called the database. Each transaction in D has a unique transaction ID and contains a subset of the items in I. A rule is defined as implications of the form $X \Rightarrow Y$ where $X, Y \subseteq I$ and $X \cap Y = \phi$ where X, Y are the items. To select interesting rules from the set of all possible rules, constraints on various measures of significance and interest can be used. The best-known constraints are minimum thresholds on support and confidence [17].

Use of a fuzzy ARM algorithm for the Generation of fuzzy association rules algorithm is not a straightforward process. Firstly, Crisp dataset must be converted into a fuzzy dataset. Second, the crisp ARM algorithm is used to calculate the frequency of an itemset just by looking for its presence or absence in a transaction of the dataset, but fuzzy ARM algorithms need to take into account the fuzzy membership of an itemset in a particular transaction of the dataset, in addition to its presence or absence.

Fuzzy ARM, like many ARM algorithms uses the support-confidence framework [6], a feature of which is that for an item set to be "frequent" its supersets must also be frequent. This downward closure property is maintained in the Fuzzy ARM algorithm. The support for a 1-itemset is simply the sum of the membership degree values divided by the number of records in the data set. The support for N-item sets, for each record containing the item set, is the sum of the products of the membership degree values in each record divided by the number of records in the data set. Thus, given a

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data set of the form having letters as attribute identifiers, and numerical value (in the range [0, 1]) representing membership value:

<c,1.0>

<a,0.5> <b,0.5>

<a,0.5> <c,0.5>

<a,0.5> <b,0.5>

The calculated support values will be:

{a} = 0.375

{c} = 0.375

{a c} = 0.0625

{b} = 0.25

{a b} = 0.125

Fuzzy Association rules generated from the previous step are used as input for the recommendation engine to generate recommendations. The recommendation engine extracts the resource attributes from page views of the active user session window and then uses association rules in order to search associated resource attributes. All these input resource attribute and associated resource attributes are used to generate recommendation set. Pages which contain the maximum of these recommended attributes are added in the final recommendation set.

V. IMPLEMENTATION

Web access log data is preprocessed as shown in figure 4. To generate fuzzy Association rules, Apriori-T package is used. Association rules are generated by using the Fuzzy ARM. Fuzzy Apriori Algorithm is implemented in the Apriori-T package. Association Rule generation using fuzzy ARM is shown in the figure 4 and 5.

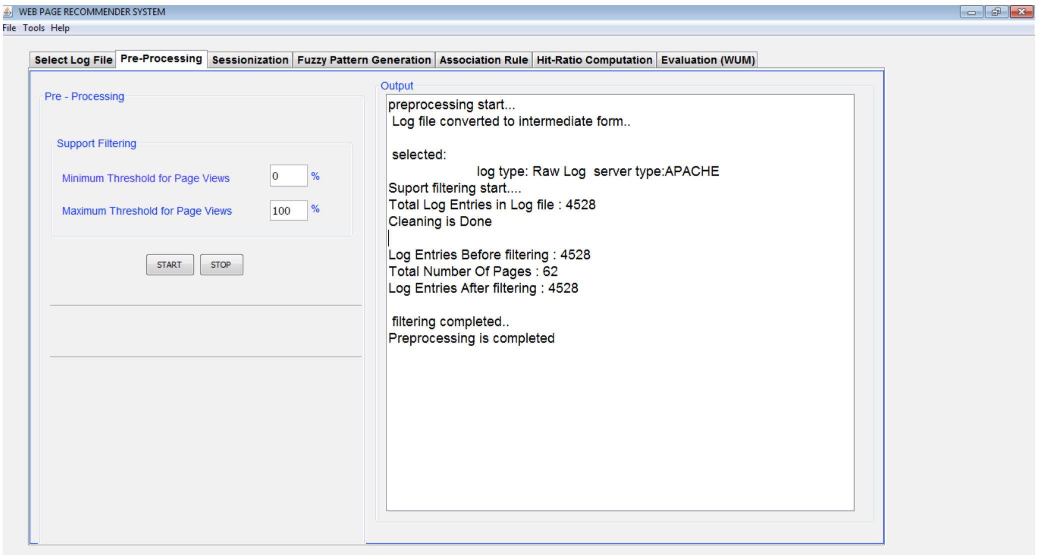

Figure 4. Preprocessing of log data

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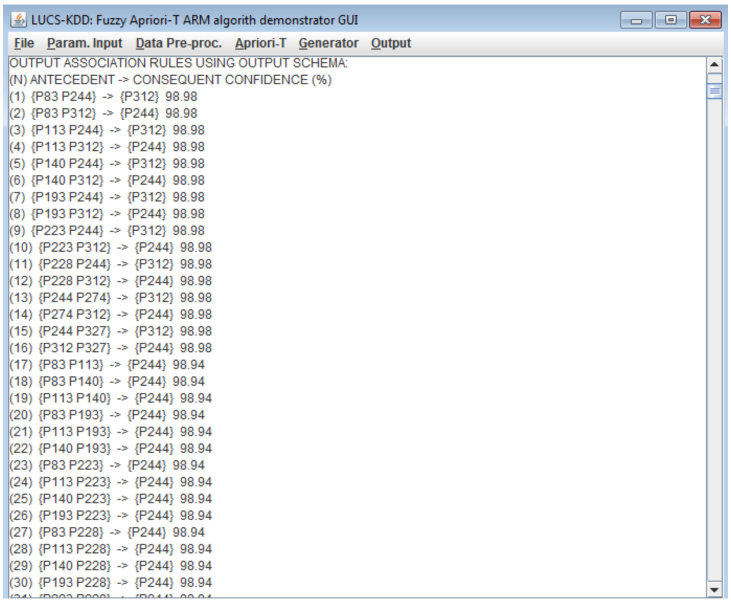

Figure 5. Sample of Generated Association Rules Using Fuzzy ARM

VI. PERFORMANCE EVALUATION

This subsection briefly describes the general results of the Recommendation system. In order to evaluate the recommendation effectiveness, the performance is measured using three different standard measures, namely, precision, coverage and F1-measure.

Assume that transaction t is viewed as a set of pageviews, and a window w of t (of size $|w|$) is used to produce a recommendation set R using the recommendation engine. Then the precision of R with respect to t is defined as:

$$Precision\ (R, t) = \frac{|R \cap (t-w)|}{|R|} \qquad (9.1)$$

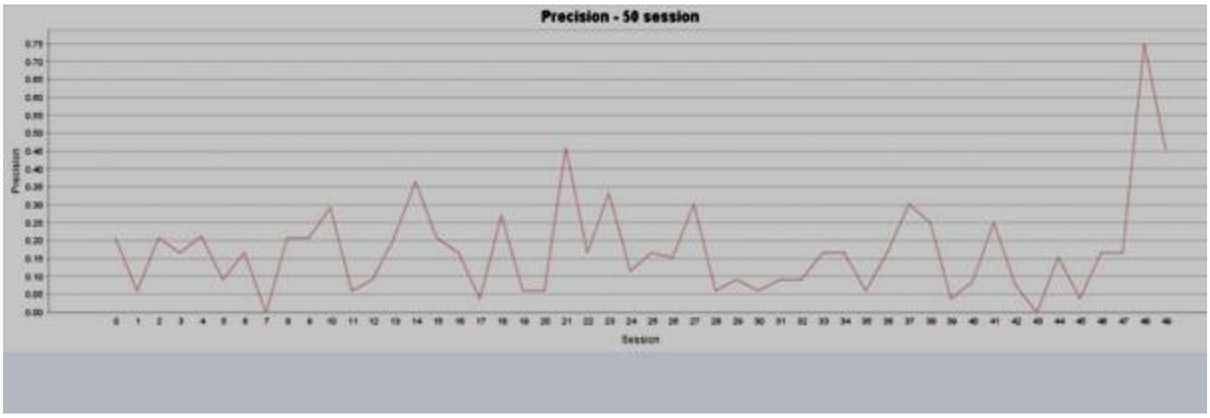

Figure 6 Precision Line Chart for 50 Sessions

The coverage of R with respect to t is defined as:

$$Coverage\ (R, t) = \frac{|R \cap (t-w)|}{|t-w|} \qquad (9.2)$$

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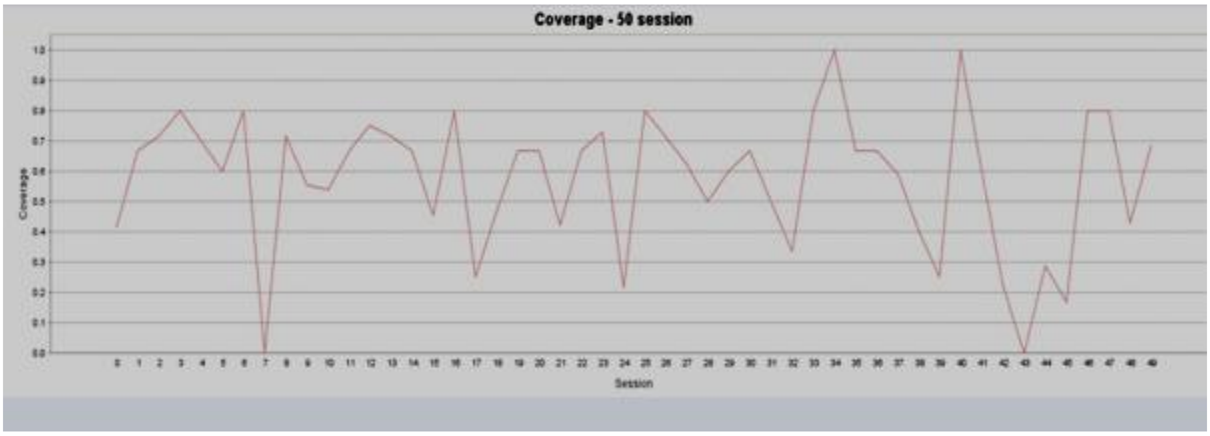

Figure 7. Coverage Line Chart for 50 Sessions

Figure 6 and 7 shows Line chart for precision and Coverage of the sample 50 sessions, for further analysis *F1*-measure is calculated as

$$F1(R,t) = \frac{2*precision \ *Coverage}{precision \ +Coverage} \qquad (9.3)$$

In this context, precision measures the degree to which the recommendation engine produces accurate recommendations i.e., the proportion of relevant recommendations to the total number of recommendations. On the other hand, coverage measures the ability of the recommendation engine to produce all of the pageviews that are likely to be visited by the user. The *F1* measure attains its maximum value when both precision and coverage are maximized. *F1* can be viewed as a measure of similarity between *R* set and *(t-w)* set.

VII. CONCLUSION

Generally Internet usage has seen tremendous growth. In the recent years, the number of Internet users globally increased from million to billion. Most of the percent of the world's population had access to computers with 1 billion searches every day. Reason behind this is the massive availability of information onto the World Wide Web has facilitated users in retrieving information. This huge availability data on the Web has made it necessary to find the ways to retrieve the information needed. Web usage mining is one of the ways to find and provide the necessary data. Web Usage Mining is used to discover the interesting user navigational patterns. These user navigational patterns are used to build the Web page recommender systems. Web page recommender systems predict users' needful information and recommend the next page to the user to facilitate their navigation. Web usage mining uses different techniques to build the Web page recommender systems.

This work focused on the recommender system. This system firstly applies preprocessing on Web access logs and extracts semantic information from Web page contents. From preprocessed Web access logs fuzzy periodic attributes and fuzzy semantic attributes with fuzzy membership values are calculated. These fuzzy attributes are given as input to fuzzy ARM to generate association rules. Recommendations are generated by using these association rules. The experimental results have shown that this System can achieve effective periodic Web personalization. In Future this approach will be extended to provide real-time recommendation on portable Web-enabled devices that are becoming increasingly popular among consumers (e.g. mobiles, Smartphone).

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