User Navigation Pattern Discovery using Fast Adaptive Neuro-Fuzzy Inference System

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Abstract

World Wide Web is a huge repository of web pages and links. It provides abundance information for the Internet users. The growth of web is incredible as it can be seen in present days. Users' accesses are recorded in web logs. From the user's perspective, it is very difficult to extract useful knowledge from the huge amount of information and secondly, it is also difficult to extract for the users to access relevant information efficiently. From business point of view, the webmasters and administrators find it difficult to organize the contents of the websites to cater to the needs of the users. Both the problems can be solved if the web navigation behavior of a user can be understood. One way to extract such information is to use Web Usage Mining. Web Usage Mining consists of preprocessing, pattern discovery and pattern analysis. Preprocessing is the step which transforms the raw log file into a form that is more suitable for mining. Four steps are used in preprocessing, they are, data cleaning, user identification, session identification and formatting the result to suit the clustering algorithm. The clustering technique used in this paper is Fuzzy-Possibilistic C-Means clustering technique. In pattern analysis, this paper uses Fast Adaptive Neuro-Fuzzy Inference System (FANFIS). The experimental results suggest that the proposed technique for web log mining results in better prediction of user behaviors when compared to the existing web usage mining techniques.

Keyword: Raw log file, Preprocessing, Fuzzy-Possibilistic C-Means, Web Usage Mining, Adaptive Neuro Fuzzy Interference System (ANFIS).

1. INTRODUCTION

World Wide Web (WWW) [9, 10], in the current era of information explosion, has become the large source of online data, which includes text, graphics, videos, sound, etc. WWW is global data medium where users read, write and communicate through computers associated with the Internet. It has become the default technology for sharing innovative schemes and content exchange. The impact of the Internet on everyday life is tremendous and it has changed the way of doing business, providing and receiving education, organization management, etc. The manner of information collection and sharing has changed with the advancement of hardware and communication software. The number of people using WWW is around 20.1 per cent in Asia alone and more than 234 million websites and 126 blogs [16] which shows the enormous growth and development of the WWW.

Thus, it can be concluded that the Web is a diverse, dynamic and unstructured data repository, which provides vast amount of useful information and also illustrates the complexity of handling huge amount of information from the different viewpoints, users, Web service providers, business analysts. The effective search tools are very much necessary to identify meaningful and useful information precisely.

The growth has inspired the web service providers to forecast the user's web usage behaviors so that, they can

(i) Personalize the information provided to them
(ii) Make the websites more user friendly
(iii) Reduce the traffic load
(iv) Create or modify their website to suit different group of people.

The application of machine learning approaches to web-based information for learning or extracting data is broadly called as Web mining [14]. The approaches in web mining concentrates on offering solutions to content provider, web designer and programmers to enhance their website and also to the web users with navigation assistance tools. It is a segment of data mining in which knowledge is obtained from WWW. This approach comprises of preprocessing, pattern discovery and pattern analysis. Pattern discovery is carried out through Fuzzy Possibilistic C-Means clustering approach. In pattern analysis, this paper uses Fast Adaptive Neuro-Fuzzy Inference System.

2. RELATED WORKS

This section reviews some proposals made in web personalization [5, 6], system and business intelligence through the use of web usage mining.

Web mining [7] has been significantly applied to several areas like research trend identification, robot detection and filtering to split human and non-human nature, user profiling, fraud and threat investigation and discovering web communities. Several tools and techniques have been proposed which examine web log data to offer knowledge that will facilitate web administrators in building effective websites. Chi et al. [1] presented a Web Ecology and Evolution Visualization (WEEV) tool to recognize the association between Web content, Web structure and Web

Usage over a period of time. Web Usage Mining [19] is the most sought after tool in the Internet community where data form online web is converted to meaningful knowledge. The knowledge [12] thus discovered can be used in web personalization, general system improvement, improve business intelligence, site modification and discover usage characteristics. Identifying usage characteristics from navigational patterns has been one of the vital areas of research.

Mobasher et al. [2] presented a potential approach for identifying user profiles depending on association rules discovery and usage based clustering integrating with present position of an on-going activity to carry out real time personalization [15]. This approach according to web usage mining provides Personalized Site Maps that are focused to the interest of each individual visitor.

Shahabi and Kashani [3] illustrated a whole structure for web-usage mining to fulfill the difficult necessities of web-personalization applications [8]. The author proposed a distributed user-tracking technique for correct, scalable, and inherent collection of the usage data [11] and presented a Feature-Matrices (FM) approach, to identify and interpret the access patterns of the users. A new similarity evaluation depending on FM was developed for correct categorization of partial navigation prototypes in real time. This proposed approach is well suited for both synthetic and real data for anonymous and efficient web personalization. A study of the popular approaches and tools presented for web personalization was provided by Eirinaki and Vazirgiannis [4]. The personalization agent employs the user model data along with the past identified sequential patterns and uses a collection of personalization [13] rules to provide the personalization works or operations like memorization of personal information, user salutation, recommendation of links connected to what users in the same category past selected or links that the same user generally views, objects separation by giving various features of each object.

3. METHODOLOGY

Data cleaning is one of the preprocessing techniques which are used to eliminate inappropriate records that are not essential for mining. Data cleaning comprises of the following steps:

- Removal of records of graphics, videos and the format information.
- Removal of records with the failed HTTP status code.
- Robots cleaning.

The unwanted and unrelated data are removed using the above steps. Knowledge extraction is the next step after the preprocessing phase. The main objective of this step is to find out the user behavior and the navigation patterns. For this purpose clustering algorithm is used. Clustering plays a significant role in data analysis and understanding the behavior of users in the websites. It combines the data into classes or clusters with the intention that the data objects inside a cluster have huge similarity in relationship to one another, but are very dissimilar to those data objects in other clusters. In this paper, Fuzzy Possibilistic C-Means Algorithm is used to find out to extract the user behavior.

The Fuzzy C-Means (FCM) [17, 18] can be regarded as the fuzzified form of the k-means algorithm. It is an approach of clustering which permits one piece of data to fit in to two or more clusters. This method is commonly used in pattern recognition. The algorithm is an iterative clustering approach that generates an optimal c partition by reducing the weighted within group sum of squared error objective function.

FPCM is an integration of both possibilistic C-Means (PCM) and Fuzzy C-Means (FCM) that are supposed to circumvent a variety of difficulties of PCM and FCM. FPCM completely ignores the noise sensitivity deficiency of FCM, overcomes the coincident clusters problem of PCM.To predict the user behavior existing approaches have been used FCM and PCM. But the existing approaches are inadequate because of its sensitivity towards noise. Thus with the help of FPCM, noise is reduced, provides more accuracy and thus provides better result in predicting the user behavior.

In the online phase, when a new request appears at the server, the wanted URL and the session to which the user belongs are determined, the primary knowledge base is restructured, and a list of implication is suggested to the demanded page. After the clustering is performed, the output will be a set of clusters np' = $<np_1, np_2, \ldots np_n>$ where np_i = $<P_1, P_2, \ldots, P_k>$ where k represents the set of web pages identified as user navigation patterns and $1 \leq i \leq n$. Sequence W' = $<P_1, P_2, \ldots P_m>$ represents a current active session and m indicates size of active session window.

The web pages present in the active session are sorted and after this the prediction list is determined by means of classification. After this process, for building the prediction list, the technique used is Fast Adaptive Neuro-Fuzzy Inference System algorithm.

The ANFIS [20] is a framework of adaptive technique to assist learning and adaptation. This kind of framework formulates the ANFIS modeling highly organized and not as much of dependent on specialist involvement. To illustrate the ANFIS architecture, two fuzzy if-then rules according to first order Sugeno model are considered:

$$Rule\ 1: If\ (x\ is\ A_1) and\ (y\ is\ B_1) then\ (f_1 = p_1 x + q_1 y + r_1)$$

$$Rule\ 2: If\ (x\ is\ A_2) and\ (y\ is\ B_2) then\ (f_2 = p_2 x + q_2 y + r_2)$$

where x and y are represents the inputs, A_i and B_i indicating the fuzzy sets, f_i indicates the outputs within the fuzzy region indicated by the fuzzy rule, $p_i, q_i and\ r_i$ shows the design parameters that are determined while performing training procedure.

The ANFIS architecture to execute these two rules is represented in figure 1, in which a circle shows a fixed node and a square shows an adaptive node.

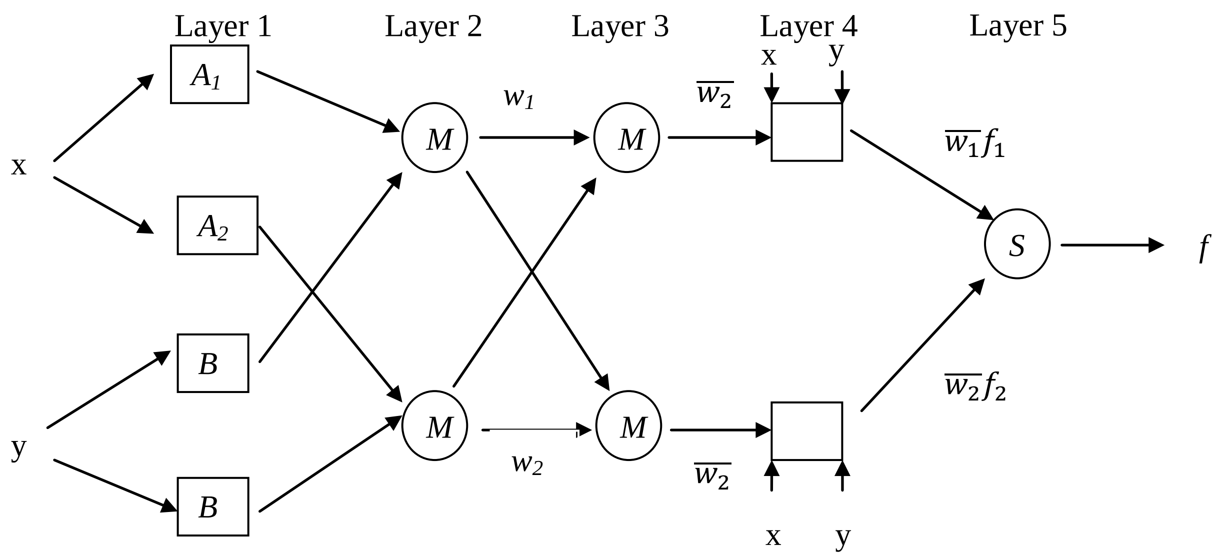

Figure 1: ANFIS Architecture

All the nodes in the initial layer are adaptive. The outcomes from these adaptive nodes are fuzzy membership grade of the inputs that are indicated by:

$$O_i^1 = \mu_{A_i}(x) \quad i = 1,2 \tag{1}$$

$$O_i^1 = \mu_{B_{i-2}}(y) \quad i = 3,4 \tag{2}$$

where $\mu_{A_i}(x), \mu_{B_{i-2}}(y)$ can allow any fuzzy membership function. For instance, if the bell shaped membership function is utilized, $\mu_{A_i}(x)$ is given by:

$$\mu_{A_i}(x) = \frac{1}{1 + \left\{\left(\frac{x - c_i}{a_i}\right)\right\}^{b_i}} \tag{3}$$

where a_i, b_i and c_i is nothing but the parameters of the membership function which controls the bell shaped functions accordingly.

In the second layer, the nodes are fixed. These nodes are named with M, indicating that they perform as a simple multiplier. The outcome of this layer can be given by:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \quad i = 1,2 \tag{4}$$

which represents the firing strengths of the rules.

Also, the nodes in third layer are fixed. They are named with N, indicating that they are occupied in a normalization function to the firing strengths from the earlier layer.

The outputs of this layer can be represented as:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{5}$$

which represents the normalized firing strengths.

All nodes that are in fourth layer are adaptive. The outcome of the entire node in this layer is just the multiplication of the normalized firing strength with the first order polynomial. As a result, the outcome of this layer is represented by:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \quad i = 1,2 \tag{6}$$

There is only one node named 'S' in the layer 5. This nodes performs the addition of all the incoming signals. Thus, the overall output of the model is given by:

$$O_i^5 = \sum_{i=1}^{2} \overline{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \tag{7}$$

It can be distinguished that layer 1 and the layer 4 are adaptive layers. Layer 1 composes of three adjustable parameters like $a_i, b_i and\ c_i$ that is related to the input membership functions.

These parameters are represented as premise parameters. In layer 4, there exists three adjustable parameters namely $p_i, q_i and\ r_i$, related to the first order polynomial. These parameters are called consequent parameters.

Learning algorithm of ANFIS

The intention of the learning algorithm is to adjust all the modifiable parameters such as$\{a_i, b_i, c_i\}$ and $\{p_i, q_i, r_i\}$, for the intention of matching the ANFIS output with the training data. If the parameters such as $a_i, b_i and\ c_i$of the membership function are unchanging, the outcome of the ANFIS model can be given by:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \tag{8}$$

Substituting Eq. (5) into Eq. (8) yields:

$$f = \overline{w}_1 f_1 + \overline{w}_2 f_2 \tag{9}$$

Substituting the fuzzy if-then rules into Eq. (15), it becomes:

$$f = \overline{w}_1(p_1 x + q_1 y + r_1) + \overline{w}_2(p_2 x + q_2 y + r_2) \tag{10}$$

After rearrangement, the output can be expressed as:

$$f = (\overline{w}_1 x)p_1 + (\overline{w}_1 y)q_1 + (\overline{w}_1)r_1 + (\overline{w}_2 x)p_2 + (\overline{w}_2 y)q_2 + (\overline{w}_2)r_2 \tag{11}$$

which is nothing but the linear display of the changeable resulting parameters like p_1, q_1, r_1 and p_2, q_2, r_2. The least squares distance method can be used to identify the optimal values of these parameters easily. If the basis parameters are not changeable, the search space turns to be larger and directs to allowing for large time for convergence. A hybrid technique combining the least squares distance measure and the gradient descent method is used for the purpose of solving this drawbacks. The hybrid algorithm contains a forward pass and a backward pass. The least squares method that functions as a forward pass is used for the purpose of determining the outcome parameters with the no alterations in the premise parameters. Once the optimal consequent parameters are identified, the backward pass starts directly. The gradient descent method that functions as a backward pass is used to fine-tune the premise parameters equivalent to the fuzzy sets in the input domain.

The outcome of the ANFIS is determined by utilizing the outcome parameters gathered in the forward pass. The output inaccuracy is used to modify the principle parameters with the help of standard back propagation technique. It has been accepted that this hybrid method is very proficient in training the ANFIS. Learning can be fast up in ANFIS using Modified Levenberg-Marquardt algorithm.

Modified Levenberg-Marquardt algorithm

A Modified Levenberg-Marquardt algorithm is used for training the neural network. Considering performance index is $F(w) = e^T e$ using the Newton method we have as:

$$W_{K+1} = W_K - A_K^{-1}.g_K \qquad (12)$$

$$A_k = \nabla^2 F(w)|_{w=w_k} \qquad (13)$$

$$g_k = \nabla F(w)|_{w=w_k} \qquad (14)$$

$$[\nabla F(w)]_j = \frac{\partial F(w)}{\partial w_j} = 2\sum_{i=1}^{N} e_i(w).\frac{\partial e_i(w)}{\partial w_j} \qquad (15)$$

The gradient can write as:

$$\nabla F(x) = 2J^T e(w) \qquad (16)$$

Where

$$J(w) = \begin{bmatrix} \frac{\partial e_{11}}{\partial w_1} & \frac{\partial e_{11}}{\partial w_2} & \cdots & \frac{\partial e_{11}}{\partial w_N} \\ \frac{\partial e_{21}}{\partial w_1} & \frac{\partial e_{21}}{\partial w_2} & \cdots & \frac{\partial e_{21}}{\partial w_N} \\ & \vdots & & \\ \frac{\partial e_{KP}}{\partial w_1} & \frac{\partial e_{KP}}{\partial w_2} & \cdots & \frac{\partial e_{KP}}{\partial w_N} \end{bmatrix} \qquad (17)$$

$J(w)$ is called the Jacobian matrix.

Then, Hessian matrix is identified. The k, j elements of Hessian matrix provides:

$$[\nabla^2 F(w)]_{k,j} = \frac{\partial^2 F(w)}{\partial w_k \partial w_j} = 2\sum_{i=1}^{N}\left\{\frac{\partial e_i(w)}{\partial w_k}\frac{\partial e_i(w)}{\partial w_j} + e_i(w).\frac{\partial^2 e_i(w)}{\partial w_k \partial w_j}\right\} \qquad (18)$$

The Hessian matrix can then be expressed as follows

$$\nabla^2 F(w) = 2J^T(W).J(W) + S(W) \qquad (19)$$

$$S(w) = \sum_{i=1}^{N} e_i(w).\nabla^2 e_i(w) \qquad (20)$$

If S(w) is small assumed, the Hessian matrix can be approximated as

$$\nabla^2 F(w) \cong 2J^T(w)J(w) \qquad (21)$$

$$W_{k+1} = W_k - [2J^T(w_k)\cdot J(w_k)]^{-1}2J^T(w_k)e(w_k)$$
$$\cong W_k - [J^T(w_k)\cdot J(w_k)]^{-1}J^T(w_k)e(w_k) \qquad (22)$$

The main benefit of Gauss-Newton is that it does not need computation of second derivatives.

There is a problem the Gauss-Newton method is the matrix $H = J^T J$ may not be invertible. This can be overcome by using the following modification.

Hessian matrix can be written as

$$G = H + \mu I \qquad (23)$$

Suppose that the eigenvalues and eigenvectors of H are $\{\lambda_1, \lambda_2, \ldots \ldots, \lambda_n\}$ and $\{z_1, z_2, \ldots \ldots, z_n\}$.Then:

$$\begin{aligned} Gz_i &= [H + \mu I]z_i \\ &= Hz_i + \mu z_i \\ &= \lambda_i z_i + \mu z_i \\ &= (\lambda_i + \mu)z_i \end{aligned} \qquad (24)$$

Thus, the eigenvectors of G are the similar as the eigenvectors of H, and the Eigen values of G are $(\lambda_i + \mu)$. The matrix G is positive definite by rising μ until $(\lambda_i + \mu) > 0$ for all i thus the matrix will be invertible.

This leads to Levenberg-Marquardt algorithm:

$$w_{k+1} = w_k - [J^T(w_k)J(w_k) + \mu I]^{-1}J^T(w_k)e(w_k) \qquad (25)$$

$$\Delta w_k = [J^T(w_k)J(w_k) + \mu I]^{-1}J^T(w_k)e(w_k) \qquad (26)$$

The learning parameter, μ denotes illustrator of steps of actual output movement to preferred output. In the standard Levenberg-Marquardt technique, μ denotes a constant number. This paper modifies LM technique using μ as

$$\mu = 0.01e^T e \qquad (27)$$

Where e denotes a $k \times 1$ matrix thus $e^T e$ is a1×1 therefore $[J^T J + \mu I]$ is invertible.

Hence, if actual output is out of range than preferred output or likewise, errors are huge so, it converges to preferred output with large steps. Similarly, when quantity of error is very less then, actual output approaches to preferred output with soft steps. Thus, error oscillation greatly minimizes.

4. Experimental Results

To evaluate the performance of the proposed FANFIS technique, numerous experiments have been conducted on the data from the UCI dataset repository (http://www.ics.uci.edu) that comprises of several logs from msnbc.com for the month of September 1998.

Every sequence related to the page views of a user throughout that 24 hour time period. Each event in the sequence corresponds to a users request for a page.

TABLE I: Sample Sequence

Sequence	Order of user page visits
1	1 1
2	2
3	3 2 2 4 2 2 2 3 3
4	5
5	1
6	6
7	1 1
8	6
9	6 7 7 7 6 6 8 8 8 8
10	6 9 4 4 4 10 3 10 5 10 4 4 4
11	1 1 1 11 1 1 1
12	12 12
13	1 1

Consider there are 17 page categories "Home Page", "News", "Technology", "Cinema", "Opinion", "Politics", "Miscellaneous", "Weather", "Health", "Living", "Business Opportunities", "Sports", "Summary", "bbs" (bulletin board service), "Travel", "Books", and "Photos".

Each category is related in sequential order with an integer starting from "1". For example, "Home Page" is numbered as 1, "News" with 2, and "Technology" with 3. Each row below "% Sequences:" describes the hits in order of a single user. For instance, the first user hits "Home Page" twice, and the second user may hits "News" once.

The first similarity upper approximation at weighting threshold (m) value 0.5 is given by

R(T1)={T1,T5,T7,T11,T13},
R(T2)={T2},
R(T3)={T3},
R(T4)={T4,},
R(T5)={T1,T5,T11,T13},
R(T6)={T6,T8},
R(T7)={T1,T7,T11,T13},
R(T8)={T6,T8},
R(T9)={T9},
R(T10)={T10}
R(T11)={T1,T5,T7,T11,T13},
R(T12)={T12},
R(T13) ={T1,T5,T7,T11,T13}

The similarity upper approximations for

S1={T1,T5,T7,T11,T13},
S2={T2,},
S3={T3},
S4={T4},
S5={T1,T5,T7,T11,T13},
S6={T6,T8},
S7={T1,T5,T7,T11,T13},
S8={T6,T8},
S9={T9},
S10={T10},
S11={T1,T5,T7,T11,T13},
S12={T12},
S13={T1,T5,T7,T11,T13}.

This indicates that user visiting the hyper links in T1 may also visit the hyperlinks in T5 and then T7, T11 and hyper links in T13. Also one who visits the hyper links in T6 possibly will also visit the hyper links in T8.

The proposed prediction accuracy is compared by means of using the sample sequence as 1-6-2, 3-7-1-10, 2-1-9-5-6, 9-2-5-7-1 and 1-3-4-2.

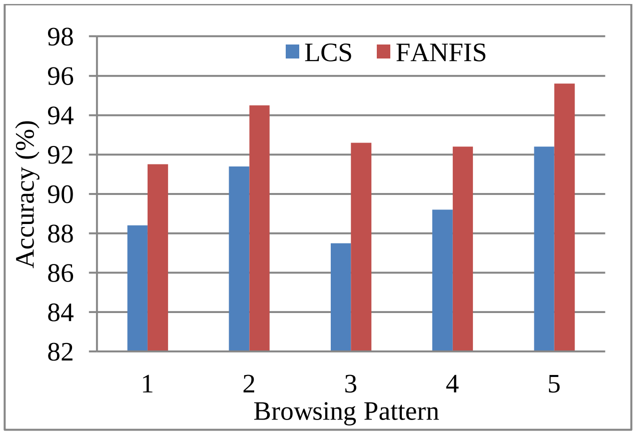

Figure 2: Accuracy of Web Page Prediction

Figure 2 represents the web page prediction accuracy by using various patterns suggested by the users. From the figure, it can be observed that the proposed technique results in better accuracy of prediction when compared to the existing technique.

5. Conclusion

Web mining is the extraction of interesting and useful knowledge and implicit information from artifacts or activity related to the WWW. Web servers record and accumulate data about user interactions whenever requests for resources are received. Analyzing the Web access logs can help understand the user behavior and the web structure. An important knowledge that can be obtained from web log files is the user's navigation pattern. The navigation pattern knowledge can be used to help users from getting loss in the cyberspace by predicting their future request. For clustering the user behavior, this paper uses FPCM clustering technique. From the clustered results, several important statistics like number of visits made to a webpage, the most popular web page among different users, common navigation pattern between users can be identified. Classification is performed in this paper using Fast Adaptive Neuro Fuzzy Interference System. Experimental results show that the proposed web usage mining technique results in better accuracy of predicting the web pages.

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