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Clustering Of Web Access Patterns for Segmenting Web Users Using a Fuzzy Based Cluster Estimation Method

Rajimol A

Department of Computer Applications, Marian College Kuttikkanam, Kerala, India

*Corresponding Author: rajimol.a@mariancollege.org

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Abstract- This paper presents a method for segmenting the web users based on their web access patterns. History of web pages visited by users includes informations like access sequences of web users and number of visits of web pages and reveals interest of users in particular pages. The web users' access patterns can be segmented to group the users with similar interests. In this work, a simple, count based technique is used for preprocessing web access data so as to convert it into a database with fixed number of attributes. A novel approach based on fuzzy clustering principles for unsupervised clustering is extended to identify the number of web user groups based on their access patterns. This method starts by assuming that all the data points are initial clusters. Pairs of similar clusters are then merged based on fuzzy membership values. This paper also compare the cluster count obtained with this approach with the cluster count obtained with Cohonen's unsupervised clustering algorithm. The tools available with IBM SPSS Modeler 14.1 are used to benchmark the quality of cluster estimation.

Keywords- Fuzzy Clustering, Web access pattern, Fuzzy Logic, k-means clustering, c-means clustering.

I. INTRODUCTION

Knowledge engineers and system analysts are now faced with challenges of maintaining a competitive edge in the world of e-commerce and rapidly changing delivery channels. To meet these challenges, they must look into the accumulated raw data to find new customer relationships, possible newly emerging lines of business and ways to cross sell existing products to new and existing customers groups [1]. Large databases in commerce driven industries, web based systems and social networking applications contain a staggering amount of raw data. Data Mining or Knowledge discovery refers to a variety of techniques that have developed in the fields of databases, machine learning and pattern recognition. The intent of these techniques is to uncover useful patterns and associations from large databases. The process of finding useful patterns and information from raw data is often known as Knowledge discovery in databases or KDD [2]. Data mining is a particular step in this process involving the application of specific algorithms for extracting patterns (models) from data.

There is a vast amount of information on the World Wide Web (WWW) and more is becoming available daily. With explosive growth of data available with the web and the so called social networking sites, discovery and analysis of useful information from such data becomes a necessity [20]. Extracting useful information from the web data is termed as Web mining. World Wide Web data can be classified in to four groups namely, content, structure, usage and user profile data [3].

Content data includes the resource (the real data) such as HTML documents, images, sound files, etc. Structure data describes the structure and the organization of the content through internal tags (intra-page) or hyper-links (inter-page). Usage data is the collection of available data describing the usage of Web resources (e.g. access logs of HTTP servers). User profile data means demographic information derived from registration [3, 16].

Based on the primary kinds of data used in the mining process, web mining tasks can be categorized into three types: web structure mining that mines web's linkage structure, web content mining that uses multimedia data on the web and web usage mining or web log mining that mine usage details of web surfers [4, 17]. Servers register a Web log entry for every single access they get, in which important pieces of information about accessing are recorded, including the URL requested, the IP address from which the request originated, and a time-stamp. Applying Data Mining techniques on this web log data can reveal many interesting knowledge about the web users [18].

In Data Mining, Cluster analysis is a technique for breaking data down into related components in such a way that patterns and order becomes visible. Clusters are natural groupings of data items based on similarity metrics or

probability density models. Clustering algorithms map a new data item into one of several known clusters [5]. Membership of a data item in a cluster can be determined by measuring its distance from each cluster center. In crisp clustering, the data item is added to a cluster for which this distance is minimal. In fuzzy clustering techniques, a data item is given partial memberships in all the clusters within a range of membership values from zero to one. A cluster has a center of gravity which is basically the weighted average of the cluster [2].

In this paper, the access sequence in web logs is modelled as fuzzy membership values in a fixed database table structure. Also, a fuzzy based algorithm is used for segmenting web users based on their interests and access patterns [15]. The server log of individual browsing records of thousands of users at *msnbc.com* is used [23].

The remaining of the paper is organized as follows; section 2 introduces the related works in this field. Section 3 is about web access data and section 4 explains k-means clustering. Section 5 introduces Fuzzy logic and section 6 is about fuzzy c-means clustering and its limitations. Section 7 explains the cluster estimation algorithm and Section 8 is about the experiments done on Web access data. Finally Section 9 concludes the paper.

II. RELATED WORK

I. V. Cadez et.al suggested in their work a new method for visualizing navigation pattern on a web site [6]. The authors presented a simple approach for clustering and visualizing user behaviour on a web site, and implemented the method in a visualization tool called WebCANVAS. They first form clusters of site users with similar navigation paths using a mixture of first-order Markov models. Then they display the behaviour of a random sample of users in each cluster along with the size of each cluster. An important feature of the model-based clustering used in the proposed work is that learning time scales linearly with sample size. The limitation of the method to model page visits at the URL level when the number of different page categories that can be requested by a user is small.

In [7], Ajith Abraham presents a novel Hybrid web usage mining method named intelligent miner. The paper proposes a hybrid framework that optimizes a fuzzy clustering algorithm. Fuzzy C-means algorithm is used to identify the number of clusters from the cleaned and pre-processed log files. The clusters are then fed to a Takagi-Sugeno fuzzy inference system to analyse the trend patterns. The if-then rule structures are learned using an iterative learning procedure by an evolutionary algorithm and a back propagation algorithm is used to fine tune the rule parameters. The proposed frame work performs better than the earlier methods for daily trends but for hourly trends its performance is low [7]. The computational complexity of the algorithm is the important disadvantage of i-Miner.

D. Cosic and S. Loncaric presented an unsupervised algorithm for cluster estimation which is a combination of fuzzy k-means algorithm and the fuzzy maximum likely hood estimation [8]. In this work maximum likely hood estimation is used to decide whether to introduce a new cluster center. The authors propose three different methods of cluster estimation for fuzzy c-means algorithm. But these methods are applicable only for segmenting CT scan images.

X. Xiong and K.L. Tan proposed a similarity driven cluster merging method for unsupervised fuzzy clustering. This method starts with over specified number of clusters and then pairs of similar clusters are merged on the basis of similarity driven cluster merging criteria [9]. The cluster merging process in the work is based on a fuzzy similarity metric. This involves the calculation of a merging threshold value each time, which is computationally expensive.

III. WEB ACCESS DATA

Web usage mining, also known as Web log mining, is process of discovering interesting access patterns of web pages from web access logs. It uses secondary data derived from interactions of users with web: web server logs, proxy server logs, user profiles, user queries, cookies [10].

A web server usually registers a web log entry for every access of Web page. It includes URL requested, IP address of the origin of request, and a time stamp. Web log database provide rich information about web dynamics [19].

Clustering analysis in web usage mining intends to find the clusters of user, page, or sessions from web log file, where each cluster represents a group of objects with common interest or characteristic. User clustering is designed to find user groups that have common interests based on their behaviors, and it is critical for user community construction [8].

User	Sequence			
1	frontpage	news	travel	travel
2	news	news	news	news
3	frontpage	news	frontpage	news
4	news	news		
5	frontpage	news	news	travel
6	news	weather	weather	weather
7	news	health	health	business
8	frontpage	sports	sports	sports
9	weather			

Figure 1. A sample access sequence

The pieces of Web logs are modelled as sequences of events to segment the users on the basis of sequential patterns over

a period of time. Each sequence is represented as an ordered list of discrete symbols and each symbol represents one of several possible categories of web pages requested by the user.

Let E be a set of events. A Web log piece or (Web) access sequence S = e1,e2,….,en (ei ∈ E) for (1≤ i ≤ n) is a sequence of events, while n is called the length of the access sequence. An access sequence with length n is also called an n-sequence. In an access sequence S, repetition is allowed. Duplicate references to a page in a web access sequence imply back traversals, refreshes or reloads For example, 1,1,2 and 1,2 are two different access sequences, in which 1 and 2 are two events[11].

Fig.1. shows a sample of such sequence. The server logs from msnbc.com for a twenty four hour period typically produce roughly one million such sequences [23]. The focus of the work described in this paper is the problem of exploring and segmenting this type of data set to group the web users based on their interests.

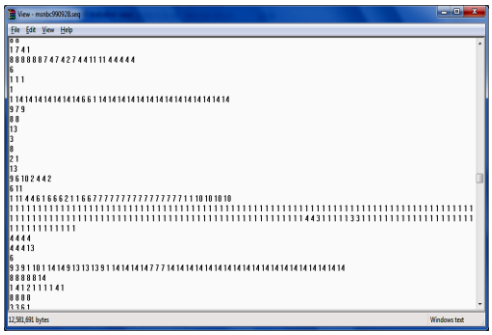

Figure 2. A portion of the web access sequence where numeric symbols are used to represent web pages

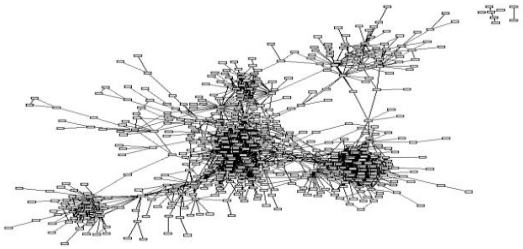

Figure 3. A graphical representation of access patterns and groups of many users, each path is an access sequence of a user and the small rectangles (nodes) represent access to a site.

IV. THE K-MEANS CLUSTERING ALGORITHM

K-means algorithm and its different variations are the most well-known and commonly used partitioning methods. The value ‘k’ stands for the number of cluster seeds initially provided for the algorithm. The technique works by computing the distance between a data point and the cluster center to add an item into one of the clusters so that intra-cluster similarity is high but inter-cluster similarity is low. A common method to find the distance is Euclidian distance [3].

V. FUZZY LOGIC

The real world data is almost never arranged in clear cut groups. Instead, clusters have ill- defined boundaries that smear into the data space often overlapping the perimeters of surrounding clusters. The modeling of such imprecise and qualitative knowledge, as well as handling of uncertainty at various stages is possible through the use of fuzzy sets. Fuzzy logic is capable of supporting, to a reasonable extent, human type reasoning in natural form by allowing partial membership for data items in fuzzy subsets [12]. Fuzzy logic is logic of fuzzy sets; a Fuzzy set has, potentially, an infinite range of truth values between one and zero. The fuzzy set is distinct from a crisp set that it allows the elements to have a degree of membership [12]. The core of a fuzzy set is its membership function: a function which defines the relationship between a value in the sets domain and its degree of membership in the fuzzy set,

$\mu = f(s, x)$ Where,

μ : is he fuzzy membership value for the element.
s : is the fuzzy set
x : is the value from the underlying domain.

Fuzzy sets provide a means of defining a series of overlapping concepts for a model variable since it represent degrees of membership. The values from the complete universe of discourse for a variable can have memberships in more than one fuzzy set. Integration of fuzzy logic with data mining techniques has become one of the key constituents of soft computing. The cluster estimation method which is used in this work[15] is developed on the foundations of fuzzy logic and fuzzy clustering.

VI. FUZZY CLUSTERING

In handling the challenges posed by massive collections of natural data. The central idea in fuzzy clustering is the non-unique partitioning of the data in a collection of clusters. The data points are assigned membership values for each of the clusters. In some cases the membership value may be zero indicating that the data point is not a member of the cluster under consideration [13].

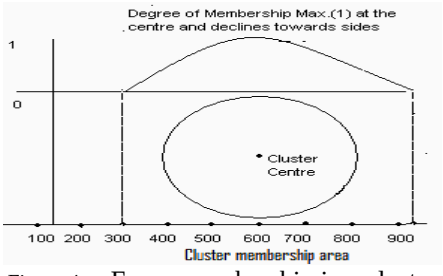

Figure 4. Fuzzy membership in a cluster

The non-zero membership values, with a maximum of one, show the degree to which the data point represents a cluster. Thus fuzzy clustering provides a flexible and robust method for handling natural data with vagueness and uncertainty. In fuzzy clustering, each data point will have an associated degree of membership for each cluster [12].

1) C-means fuzzy clustering algorithm

Fuzzy c-means clustering involves two processes: the calculation of cluster centers and the assignment of points to these centers using fuzzy membership values. This process is repeated until the cluster centers stabilize. The algorithm is similar to k-means clustering in many ways but incorporates fuzzy set's concepts of partial membership and forms overlapping clusters to support it. The algorithm needs a fuzzification parameter m in the range [1, n] which determines the degree of fuzziness in the clusters [12]. The algorithm calculates the membership value μ with the formula,

$$\mu_j(x_i) = \frac{\left(\frac{1}{d_{ji}}\right)^{\frac{1}{m-1}}}{\sum_{k=1}^{p}\left(\frac{1}{d_{ki}}\right)^{\frac{1}{m-1}}}$$

Where,

$\mu_j(x_i)$: is the membership of x_i in the j^{th} cluster
d_{ji} : is the distance of x_i in cluster c_j
m : is the fuzzification parameter
p : is the number of specified clusters
d_{ki} : is the distance of xi in cluster C_k

The new cluster centers are calculated with these membership values using the equation;

$$c_j = \frac{\sum_i \left[\mu_j(x_i)\right]^m x_i}{\sum_i \left[\mu_j(x_i)\right]^m}$$

Where,

C_j : is the center of the j^{th} cluster
x_i : is the i^{th} data point
μ_j : the function which returns the membership
m : is the fuzzification parameter

This is a special form of weighted average. The degree of fuzziness in xi's current membership is modified and multiply this by xi. The product obtained is divided by the sum of the fuzzified membership.

2) Limitations of the algorithm

The fuzzy c-means approach to clustering suffers from several constrains that affect the performance. The main drawback is from the restriction that the sum of membership values of a data point xi in all the clusters must be one as in equation (2), and this tends to give high membership values for the outlier points [14].

$$\sum_{j=1}^{p} \mu_j(x_i) = 1$$

So the algorithm has difficulty in handling outlier points. Secondly, the membership of a data point in a cluster depends directly on its membership values in other cluster centers and this sometimes happens to produce unrealistic results [12]. In fuzzy c-means method a point will have partial membership in all the clusters. The third limitation of the algorithm is that due to the influence (partial membership) of all the data members, the cluster centers tend to move towards the center of all the data points [12].

In view of these limitations, a modified c-means algorithm [14] was proposed and this modified c-means method is used for the development of the fuzzy based unsupervised clustering method [15]. The new method is considering all the data points as cluster centers initially, and later these clusters are merged on the basis of fuzzy membership values. Due to the limitation imposed by the expression (2), membership values generated by c-means algorithm is too low with large number of clusters. So the algorithm needs to be modified to handle such situations.

In C-means, the membership of a data point in a cluster depends directly on the sum of distances of the point from other cluster centers (expr. 1). Instead, the sum of distances of data members in a cluster is considered for the calculation of memberships in that cluster, it is improving the performance of the algorithm [14]. This was leading to the modification of the algorithm. The new modified membership function for i^{th} data point in j^{th} cluster is given below,

$$\mu_j(x_i) = n * \frac{\left(\frac{1}{d_{ji}}\right)^{\frac{1}{m-1}}}{\sum_{i=1}^{n}\left(\frac{1}{d_{ji}}\right)^{\frac{1}{m-1}}}$$

With the new membership method the sum of memberships of a data point in all the clusters now becomes n (number of points). So this expression can handle large number of cluster centers.

VII. THE NEW MODIFIED CLUSTERING ALGORITHM

The fuzzy based unsupervised clustering algorithm converges to the optimum number of clusters in a single step and it requires only one threshold value [15]. The algorithm does not require the user to provide the number of clusters as

an initial parameter and it doesn't also require the user to initialize the cluster centers based on the general distribution of data. The algorithm works in a single step and initially it assumes that all the data points as cluster centers. The method then uses one threshold value and it is the cluster center membership threshold (β). It is used to delete (merge) a cluster if it has a membership value greater than this in any of the other existing clusters. If a cluster center has a membership value greater than β with any other existing cluster center then it means that it is strongly associated with another cluster and one of the cluster centers can be deleted(both the clusters can be merged).

The experiments showed that initializing β to .5 (half of maximum fuzzy membership) produces desired outputs with natural data since the values are normalized. After starting with n initial centroids, the fuzzy memberships of all the points in the other clusters are found. The sums of the distance to all the points from the cluster centers are also calculated. It is found that, a centroid situated at the center of a group of points will have minimum sum of distance to other data points. A centroid which is away from a group of points will have maximum sum of distance. The centroids are selected in the descending order of sum of distances for deletion. So the new centroids which are away from the groups of points (clusters) are considered for deletion first. Such centroids are deleted if it has a fuzzy membership of at least β in any other existing clusters. Otherwise the point is treated as an outlier point.

TABLE 1. THE NEW CLUSTERING ALGORITHM

initialize m=fuzzification parameter
initialize n=the number of data points
initialize $C1=x_1, C2=x_2, \ldots Cn=xn$
//(initialize all the points as centroids)
initialize p=n
initialize β=.5
For i=1 **to** p
{
Update $\mu_p(x_i)$ for each data points applying **(**eqn 3)
Find the sum of distances for all data points in C_p

Sort cluster centers based on sum of distances
}
For each cluster center C_i in the descending order of sum of distances
{
If μ(Ci)>= β in any of the remaining cluster centers then
Delete C_i and the corresponding membership values
Update cluster center indexes
p=p-1
}

When cluster deletion process is continued like this, only the new centroids situated at the middle of clusters and the extreme outlier points will be remaining. The algorithm ends by finding the natural cluster centers and extreme outliers in the dataset.

VIII. THE EXPERIMENT AND EVALUATION

The Data used for the experiment comes from Internet Information server (IIS) logs for msbc.com and news related portions of msn.com for one entire day[16]. Each sequence in the data set corresponds to page views of a user during that day. 1500 random samples are selected. Each event in the sequence corresponds to a request for a page. Requests are recorded only at the level of page category. There are 16 categories of pages and these categories are given numeric codes from 1 to 16. The pages are included into one of these categories based on their content. These categories are front page(1), news(2), technology(3), local(4), opinion(5), on-air(6), miscellaneous(7), weather(8), health(9), living(10), business(11), sports(12), summary(13), bbs(14), and travel(15), msn-news(16) [6]. Although many other information pertaining to the web access are available, only the categories of page requests are modelled.

TABLE 2 A PORTION OF THE DATABASE CREATED BASED ON FREQUENCY COUNT

1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
0	1	2	0	0	0	0	0	0	0	0	0	0
3	0	1	5	4	0	1	4	0	0	0	0	0
0	1	0	0	0	0	0	0	0	3	2	1	2
2	2	2	1	0	0	2	0	0	4	4	0	0
4	2	0	0	0	0	3	2	2	2	0	0	0
3	3	0	0	0	0	0	1	1	2	2	0	0
1	0	0	0	0	0	0	0	0	0	0	2	2
1	0	1	1	2	12	14	0	0	0	0	0	0
4	1	3	2	2	2	0	0	0	0	0	0	0
13	2	1	2	2	3	3	3	3	2	12	0	0

To preprocess the access patterns and to convert it into a database table, the frequency of each web category in every sequence is found. A database table is created with 16 attributes with one record created for each user session. Then for each user session, the frequency of all web categories is calculated and the frequency counts are entered into corresponding column positions. Now each record of this table represents the number of occurrences of different categories of web pages in each user session. All the access patterns are brought in to this fixed table structure with frequency count values to apply clustering algorithms.

In the next step cluster estimation algorithm is applied to the newly formed database. The algorithm was implemented in Visual Basic and it converged to 9 clusters. It shows there are

9 user groups with similarities in their access patterns. Next k-means algorithm is applied to the data set with k equals 9. The popular data mining tool IBM SPSS modeler 14.1 is used for running k-means algorithm.

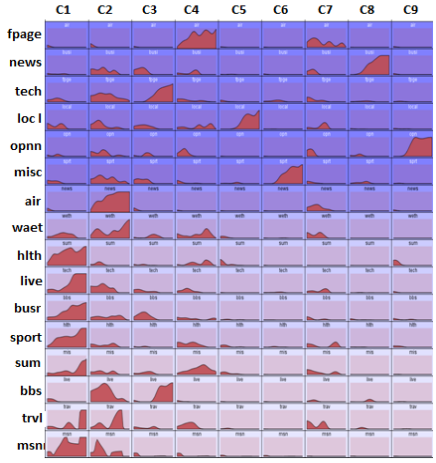

Figure 5. The nine clusters formed using IBM SPSS modeler 14.1 and k-means algorithm

It showed that the cluster quality of these 9 clusters is fairly good and the graphs represent the contributions of each field to these clusters. As it is evident from the graphical representation, Cluster1 contains web users mainly interested in health, living, business, sports and msn-news. Cluster 2 contains users interested in air, weather, BBC and msn-news. Cluster 3 users are interested in technology and bbs. Similar grouping can be found from the remaining clusters also. To compare the quality of cluster estimation, Kohonen's algorithm is applied and the algorithm converged to 12 clusters. This is an unsupervised clustering algorithm which can automatically detect the number of clusters from the data set.

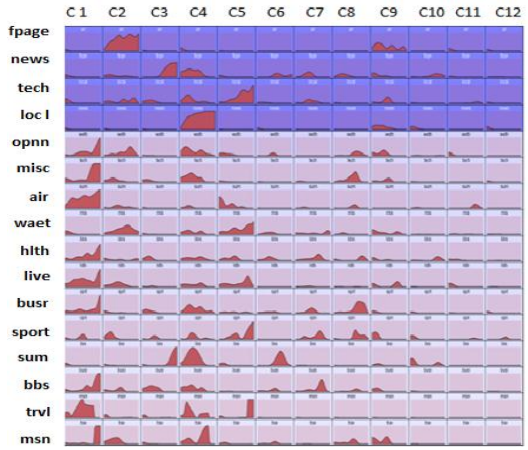

Figure 6. The twelve clusters formed using IBM SPSS modeler 14.1 and Kohonen's algorithm

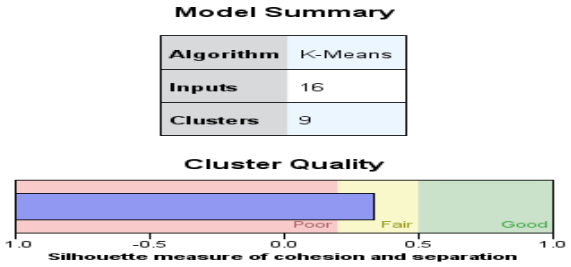

Figure 7. Cluster quality with 9 clusters

From the graphical representation it can be found that only first 9 clusters are relevant. The remaining 3 clusters do not have any significant contributions from any of the web pages.The following graphs shows the clusters quality in both k-means with 9 clusters and Cohonen's Algorithm with 12 clusters. These are generated with IBM SPSS Modeler 14.1.

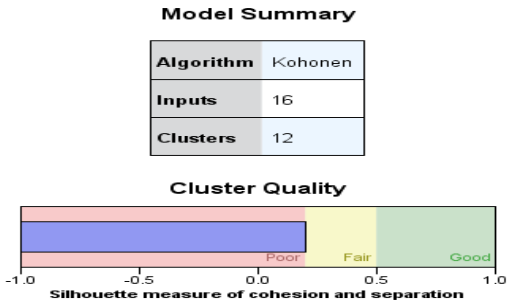

Figure 8. Cluster quality with 12 clusters

So it is evident from the study that the cluster count estimation done by the proposed algorithm is optimum. The algorithm identified 9 clusters and the cluster quality of segmentation of the data with 9 clusters is much better than that with 12 clusters. The algorithm is capable of identifying natural groups from web access patterns.

IX. CONCLUSION

In web mining, clustering of users should be tackled by exploiting inter-session access similarities of web users. The patterns identified from such clustering process can be used for web personalization and community construction. Cluster discovery is very useful in getting the preference and behavior pattern of users for web pages. Estimating the number of clusters for modeling natural data is the biggest challenge faced by the traditional supervised clustering algorithms. In this paper, a novel fuzzy based unsupervised cluster estimation method has been used in segmenting the web access data. It is found that it can detect the natural groupings of web users. These days, devising such clustering techniques is important to find user groups that have common interests based on their behaviors, and it is critical for user community construction. Knowledge of user

behavior also useful for inferring user demographics to provide personalized web content to the users.

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Authors Profile

Rajimol. A received her Bachelor degree in Mathematics from Mahatma Gandhi University, Kottayam, Kerala, India in 1990, a Master degree in Computer Applications from Anna University, Guindy, Madras, India in 1993 and Doctoral Degree from Mahatma Gandhi University, Kottayam, Kerala, India in 2014. She is currently working as Associate Professor in the Department of Computer Applications in Marian College, Kuttikkanam (Autonomous), Idukki, Kerala, India. She has 23 years of teaching experience. She serves as a member in Academic council, Faculty of Science and Technology and various Board of Studies in Mahatma Gandhi University, Kottayam, Kerala, India. Her area of interest is Data Mining, Web Mining and Image Processing. .

