

Fuzzy Classification Techniques for Online Advertisement Based on User's Perception in Social Networks

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ABSTRACT

Previously, the advertisement was done in an entirely different manner. Since technology takes over every field, now even advertisement is done through it with the help of internet. There are several websites which were initially supposed to use as socially but over the years, the advertisement is being started on them. Due to this new trend of online marketing it has become a big industry and marketers or advertisers are eagerly interested in showing ads which are well-targeted. This research presents a brief discussion regarding targeted advertisement in social network. In order to display online advertisement in social networks according to user's interest a machine learning approach, fuzzy classification analysis will be used. In fuzzy classification of users, a user can belong to more than one group in the same time. Compared to other hard clustering techniques, this method is more appropriate and suitable for user's classification of social networks.

Keywords: *Fuzzy Clustering, Online Advertisement, Social Networks, Fuzzy C-Means, Targeted Advertising.*

1. INTRODUCTION

This research analyse the interest of the users of social network and its integrations as well as the incorporation of the online advertising with the approaches of fuzzy clustering. This study make an attempt to re-evaluate the methods that have been implemented in the online advertising field and the users' interest. From the studies, it has been identified that online advertisements are a business industry core subfield where the goal and objectives of advertising hold both different commitments and challenges[1]. It is also supporting the rich data, and that can be transported to permit the aiming advertisements. Also, it is challenging because of the system of online advertising which is extremely complicated and where the advertisement delivery and attaining the information can contain various players of the industry, as compared to search advertisements. Online marketing has established very quickly over the last few years, with the real-time

bidding exchanges creations that in the real time sale for allocating the advertisements. This creates a competent approach for the advertisers to target ads to the precise users of social networking sites. From this research it is identified that classification of web users is an essential task for targeted advertising. Fuzzy clustering is a suitable method to stimulate the categories of social network users via capturing the same interests of users from the web usage information accessible in the log files [3].

1.1 Targeted Advertising on Social Networks

Targeted advertising is the one of the types of advertising through which the ads are located so as to reach the different users and founded on the different features, for instance, behavioural variables, demographics, and psychographics, etc. Social networking advertising is a group of terms that are employed to explain the online advertising forms that emphasis on the social networking services. One of the main advantages of such type of advertising is that the marketers can take benefit of the demographic information regarding users and also target their ads suitably [2]. Targeted advertising on the social network present options of targeting like behavioural targeting, psychographic targeting, geo targeting, etc., to make the widespread aim group recognition possible. With the targeted advertising on the social networks, ads are distributed to the web users founded on the data collected from the profiles of the target group. Social network's targeted advertising is not essentially the same as the social media advertising. Targeted advertising on the social networks is an approach to optimise the publicity of the social network by employing the users profile information to deliver ads directly to the web users. Such advertising refers to the procedure of harmonising the social network or web users to the target groups that have been precise by the marketers.





Fig. 1. Social Network Users Targeted Group [5]

2. FUZZY CLASSIFICATION OF USERS

Categorising the web users in the customised setup is awkward because of the exceptional nature of the dynamism in the browsing history of the user. This changing nature of the user interest and the user behaviour shall be well illustrated in the fuzzy settings. Searching through websites shows an essential part of the internet activity. There are three essential methods to the web search, first the web directories, second the hyperlinks third and last is the search engines. Though, neither of these conventional procedures of search is effectually made to manage interest of the users and also their shift in the search interest. Information available on the internet is heterogeneous, dynamic and quickly augmenting, moved out and customised. It is not self organised and un-structured as well, so surfing required data that is dangling. During the process of searching the users lean to have all the information, also read the topics in the sets of outcome, recover the document, observing the topics list linked to their issues and also navigating via websites.

Web users often spend time just to read and browse the irrelevant files and persist to spend their important time until they get the satisfactory outcomes. The main cause behind this nature is that it is complicated to comprehend the search intention of the web user; and in nature it is fuzzy. The above-given web user based parameters of web user based have the fuzziness because of the dynamism in their interest also their intention's shifting nature from one group to another. To forecast the interest of the web user these parameters of fuzzy nature, customising the search process needs useful and precise new model of a user which integrates a fuzzy classification approach. The fuzzy classification model must be employed to overcome the fuzziness from the different parameters of users and precisely forecast the class of the web user's interest also the shift of interest between the different needs of users [4].

3. FUZZY LOGIC AND ITS FOUNDATIONS

3.1 Fuzzy Set

This fuzzy logic deals with the concept of a fuzzy set. It is a set without an unclearly defined body. It is consist of elements based on the only partial degree of membership.

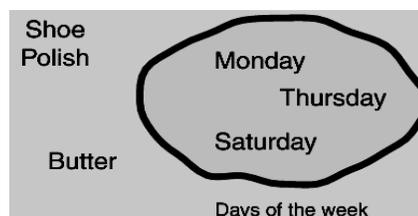


Fig. 2 Classical Set of Days of the Week

The concept of fuzzy set needs to be understood by the definition of a classical set. The classical set is the container which entirely includes or excludes any given component. For example in Figure 2, the set of days within a week undoubtedly includes Monday, Thursday and Saturday, which unquestionably exclude butter, shoe, and polish. It has discussed above that crisp sets with sharp boundaries; on the other hand, the fuzzy set is a set with smooth boundaries.

E.g. A set of the element which is partially belongs to that set.

E.g. 60% are not belonging while 40% belongs to some particular set.

It suggests besides that not belonging and to belonging other possibilities are also exists linking between a set and an element that depends upon the membership degree.

3.2 Fuzzy logic

It is the study of ambiguous, imprecise and imperfect knowledge; it is the kind of many-valued logic where the correct values of variables may be related to the real number between 1 and 0 or the truth value further may be range between entirely true or false. For example producing the function of membership for speed, three examples can be seen of membership function in the interval from 0 to 70 (mph). The degree of membership can be defined by the three functions of given speed regarding the sets of medium and fast speed.

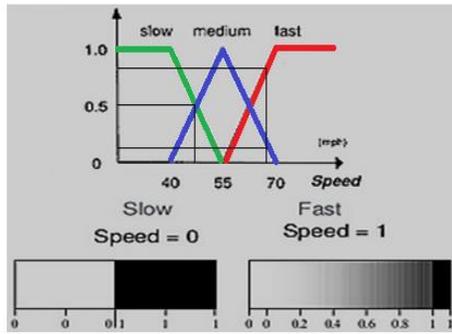


Fig. 3. Membership functions for speed slow, medium and fast

Further, for example Figure 3, if the speed of the car is 68 mph, it is the degree of membership within the set of slow speed which is 0.0, in the medium speed set 0.2, and in the fast speed set is 0.8.

4. FUZZY CLUSTERING

The Fuzzy clustering algorithm which is used to divide the social network users into the category of $1 < N < D$ classification, provides the estimate of an individual user's cluster membership values and simultaneously estimate the cluster centre. These membership value are between 0 and 1 (**can be obtained** by using eq.(1)), indicates the degree of interest of users in each cluster.

$$\mu_{ij} = \frac{1}{\sum_{k=1}^N \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \quad (1)$$

For example, the value of membership regarding μ_{ij} presents the membership degree of an individual social network user i with online advertisement cluster j .

The constraints are as follows:

$$0 \leq \mu_{ij} \leq 1, \quad \forall s, i, \quad (a)$$

$$\sum_{i=1}^c \mu_{ij} = 1, \quad \forall i. \quad (b)$$

First condition (a) ensures that the membership degrees are between 0 and 1. And second condition (b) highlights the membership degrees of an individual across the segments sum to one. In Figure 4 users' membership value is seen as the diverse category of online advertisement.

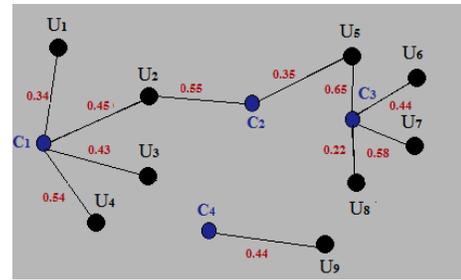


Fig. 4. Weighted User Interest Graph as a Bipartite Graph

5. FUZZY C-MEANS (FCM) ALGORITHM

The clustering method Fuzzy c-means (FCM) allows each data points belongs to several clusters with varied degrees of membership. It is based on the minimization of the following (eq. (2)) objective function.

$$J_m = \sum_{i=1}^D \sum_{j=1}^N \mu_{ij}^m \|x_i - c_j\|^2, \quad (2)$$

Where

- The number of the data point is D .
- The number of cluster is N .
- For controlling the degree of fuzzy overlap, (m) is the fuzzy partition matrix component, with $m > 1$. This is the number of data points that have important membership value in more than one cluster.
- x_i is i th data point.
- c_j is j th center of the cluster.
- μ_{ij} represents the degree of membership value of x_i in the j th cluster. The total of the membership values for all clusters is one.

5.1 The Following Steps of FCM Performs During Clustering

- 1) The cluster membership values μ_{ij} initialized randomly.
- 2) Calculating the centers of cluster by using following eq. (3).

$$c_j = \frac{\sum_{i=1}^D \mu_{ij}^m x_i}{\sum_{i=1}^D \mu_{ij}^m} \quad (3)$$

- 3) Update μ_{ij} Membership value according to eq. (1).

$$\mu_{ij} = \frac{1}{\sum_{k=1}^N \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \quad (1)$$

- 4) Calculating the objective function, J_m .
- 5) Repeating the steps 2–4 until J_m shows improvement less than defined minimum threshold or after until the maximum specified numbers of iterations.

6. CATEGORIZING SOCIAL NETWORK ADVERTISEMENT

Along with characteristics, the online social network advertisement can be divided into six main categories.

- I. **COM-ads:** telecommunication, information, and computer related ads.
- II. **MAG-ads:** newspaper ads and magazine news related.
- III. **ECO-ads:** stock, banking and business related ads.
- IV. **SPO-ads:** sports-related ads.
- V. **ENT-ads:** entertainment-related and hobby ads.
- VI. **RAN-ads:** random ads.

7. FUZZY CLASSIFICATION OF SOCIAL NETWORK USERS BASED ON ONLINE ADS

Fuzzy C-Means (FCM) Algorithm is used through MATLAB in order to analyse the interest of user in online advertisement categories with the help of following user data set.

A	B	C	D	E	F	G	H	I	J	K	L	M
Users	MAG-Ads	MAG-T	ECO-Ads	ECO-T	COM-Ads	COM-T	SPO-Ads	SPO-T	ENT-Ads	ENT-T	RAN-Ads	RAN-T
1	5	3	0	0	5	2	1	2	1	1	2	2
2	2	4	4	3	8	5	2	3	0	4	3	4
3	2	2	3	4	1	2	7	3	6	5	4	3
4	4	3	5	2	0	0	7	3	1	3	0	0
5	5	4	1	1	5	4	7	2	2	3	1	4
6	5	2	8	3	0	0	0	7	2	0	0	0
7	3	4	0	0	4	4	3	4	7	3	2	3
8	4	5	6	2	5	3	2	5	7	4	0	0
9	0	0	1	3	2	4	9	3	0	3	4	4
10	1	2	2	4	0	0	7	4	3	3	5	5
11	0	0	7	1	6	5	5	5	2	4	5	5
12	2	4	7	5	3	5	8	5	9	2	2	3
13	0	0	7	5	8	5	3	4	7	3	3	4
14	4	2	0	0	5	4	9	3	5	4	4	3
15	5	5	3	2	7	3	2	4	8	4	5	4
16	5	3	2	3	1	4	7	5	3	3	2	5
17	2	4	9	4	0	0	3	2	9	2	4	2
18	3	5	7	2	5	4	1	3	2	3	0	0
19	4	2	5	3	5	5	7	2	7	3	0	0
20	5	4	8	4	3	3	3	2	3	3	3	5
21	2	3	3	1	7	4	5	3	1	4	2	4
22	4	2	9	3	5	5	9	4	7	3	7	3
23	0	0	2	4	7	5	3	4	3	4	5	3
24	0	0	7	5	8	5	0	4	5	3	7	5
25	3	5	3	5	2	3	7	5	9	4	9	4
.
.
.

Fig. 5 Snapshot Represents the Sample User Data

Where

- Column B, D, F, H, J & L represents the frequency of online ads category hit.
- Column C, E, G, I, K & M represents the viewing time of online ads with respect to the following criteria.

Discrete Numbers	Web-Browsing Time Range
1	0s<browsing-time<=5s
2	5s<browsing-time<=10s
3	10s<browsing-time<=60s
4	60s<browsing-time<=180s
5	180s<browsing-time

Table 1: Ads Viewing Time Range

8. FUZZY C – MEANS CLUSTERING IN MATLAB

With the help of FCM function fuzzy cluster in MATLAB can be found which is given below.

[center, U, obj_fcm] = fcm(data,cluster_n,options)

8.1 Description of Function

Following is the description of the FCM function.

a) Input Arguments:

- I. *Data (Matrix):* A lot of data to be clustered, each line explains a point in a multidimensional feature space;
- II. *Cluster_n (Integer):* Total number of clusters, specified as an integer greater than 1.
- III. *Options (Vector):* Clustering options, specified as a vector with the following elements.
 - Options(1): The exponent of the fuzzy partition matrix U, particularized as a scalar greater than 1.0. Default (m = 2.0).
 - Options(2): Larger number of iterations, particularized as a positive integer. Default (100).
 - Options(3): Less improvement regarding objective function between two consecutive iterations, particularized as a positive scalar. Default (1e-5).
 - Options(4): Displayed information indicates whether to show objective function J_m value after every iteration, categorize as follows: Default (1) .



- If any factor of options is set to NaN, default value for that option is used.
- b) **Output Arguments:**
- I. *Centers (matrix)*: the centers of the cluster matrix consist of the center coordinates of the individual cluster.
 - II. *Membership_U (matrix)*: Clusters membership matrix.
 - III. *ObjFunc (vector)*: Objective function values for every iteration, returned as a vector.

8.2 Executing the FCM Function

Execute the FCM function with the help of following Matlab code.

```
Set_options = [NaN; % exponent partition matrix U
100; % max. number of iteration
0.001; % min. amount of improvement
1]; % info display during iteration
options = Set_options;
data = load('fbdatac.dat'); % load data
n_clusters = 6; % number of clusters
[center,U,obj_fcn] = fcm(data, n_clusters,options);
```

Number of Iteration Count Value of the Obj. Function

```
Iteration_count = 1, obj_fcn = 575.325513
Iteration_count = 2, obj_fcn = 441.591093
Iteration_count = 3, obj_fcn = 432.272222
Iteration_count = 4, obj_fcn = 420.187948
Iteration_count = 5, obj_fcn = 409.733745
Iteration_count = 6, obj_fcn = 404.018426
Iteration_count = 7, obj_fcn = 401.565495
Iteration_count = 8, obj_fcn = 400.535248
Iteration_count = 9, obj_fcn = 400.038774
Iteration_count = 10, obj_fcn = 399.729738
.
.
.
Iteration_count = 34, obj_fcn = 396.846404
Iteration_count = 35, obj_fcn = 396.844648
Iteration_count = 36, obj_fcn = 396.844536
```

The objective function has improved by less than 0.001

among the two final iterations obj.fcn = 396.844386 and obj.fcn = 396.844386 so the optimization has stopped.

9. OBJECTIVE FUNCTION PLOT

To view the progress of the clustering, we draw the plot of the objective function with the help of following Matlab code.

```
figure
plot(obj_fcn)
title('Objective Function Values')
xlabel('Iteration Count')
ylabel('Objective Function Value')
```

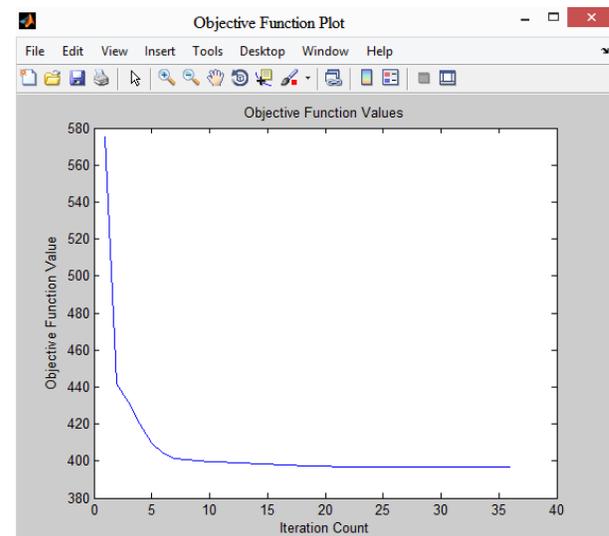


Fig. 6 Objective Function Plot

As shown in above Figure 6 the optimization has stopped after 36 iterations because obj_fun improved by less than 0.001 in final two iteration.

10. CLUSTER MEMBERSHIPS MATRIX

Table 2 shows first 10 user's degree of membership matrix with different online ads category.

User	MAG-Ad	ECO-Ad	COM-Ad	SPO-Ad	ENT-Ad	RAN-Ad
1	0.0589	0.3362	0.1607	0.2696	0.0459	0.1288
2	0.0935	0.2859	0.1887	0.2529	0.0635	0.1156
3	0.4822	0.0543	0.1168	0.0753	0.2398	0.0317
4	0.4054	0.0665	0.1198	0.0853	0.2864	0.0366

5	0.2315	0.0413	0.0866	0.0570	0.5601
6	0.2899	0.1175	0.1725	0.1427	0.2145
7	0.0769	0.3016	0.1678	0.2389	0.0671
8	0.2604	0.1109	0.2109	0.1573	0.2084
9	0.2659	0.1049	0.2172	0.1419	0.2009
10	0.2790	0.1111	0.2458	0.1569	0.1462

Table 2: Membership Values

11. USER MEMBERSHIP PLOT WITH DIFFERENT ONLINE ADS CATEGORIES

The membership matrix has plotted to view the degree of first 10 user's interest by using following Matlab code.

```
figure
plot(U')
title('User Membership Plot with Online Ads Categories')
xlabel('Number of Cluster ')
ylabel('Membership Grades')
```

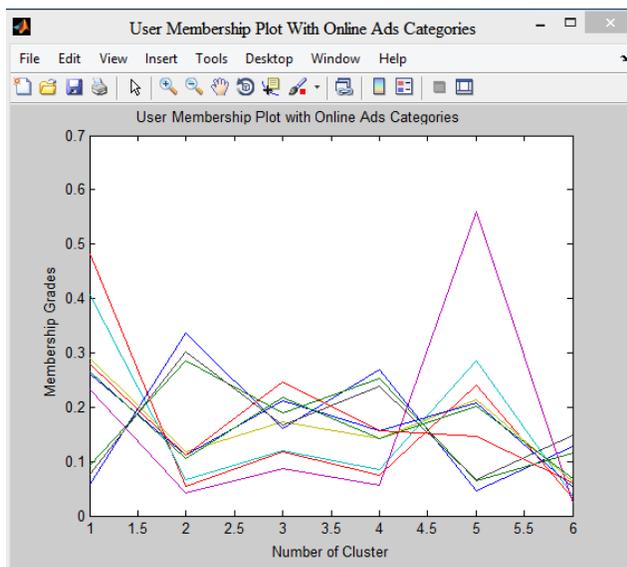


Fig. 7 Membership Matrix Plot

Each line in above graph shows the interest of first 10 individual users in each online advertisement category.

12. CLASSIFY EACH USER INTO THE CLUSTER WITH THE LARGEST MEMBERSHIP VALUE

Every user has classified into the cluster who have the largest membership degree by using following Matlab code.

```
%find max membership value of all user
>> maxU = max(U);
%find max membership value present in ad cat.1
index1 = find(U(1, :) == maxU);
index2 = find(U(2, :) == maxU);
index3 = find(U(3, :) == maxU);
index4 = find(U(4, :) == maxU);
index5 = find(U(5, :) == maxU);
index6 = find(U(6, :) == maxU);
```

```
>> maxU
0.3362 0.2859 0.4822 0.4054 0.5601 0.2899
0.3016 0.2604 0.2659 0.2790
>> index1
3 4 6 8 9 10
>> index2
1 2 7
```

The largest membership value of 10 users can be seen by **maxU** with diverse online ads category and users 3, 4, 6, 8, 9, & 10 shows in **index1** which has the largest value of membership in category of same ads (**MAG-Ads**) further they can be divide into one cluster according to **index2** shows user 1, 2 & 7 also have the largest membership value in same category of advertisement (**ECO-Ads**) and they can be classify into one cluster as well.

13. ADJUST DEGREE OF FUZZY OVERLAP IN FCM CLUSTERING BY RE-EVALUATING IMPACT OF EXPONENT PARTITION MATRIX PARAMETER VALUE (M)

As mentioned above every user is classified into a cluster according to the highest membership value as highlighted by **maxU**. If highest membership value of any user is shown in multiple clusters than how to classify those users into a cluster? For example, the maximum value of membership is up to 0.5 which indicates that the user belongs to multiple clusters equally.

```
>> index3 = find(max(U) <= 0.5)
```



1 2 3 4 6

Further, **index3** shows first five users with maximum value of membership which is equal to or less than 0.5 and they can be divided into more than one cluster as shown in Figure 8.

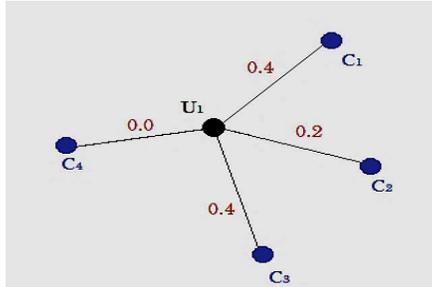


Fig. 8 User Interest Graph

Users with low maximum membership values highlight the greater degree of fuzzy overlap in the clustering result as shown in Figure 9.

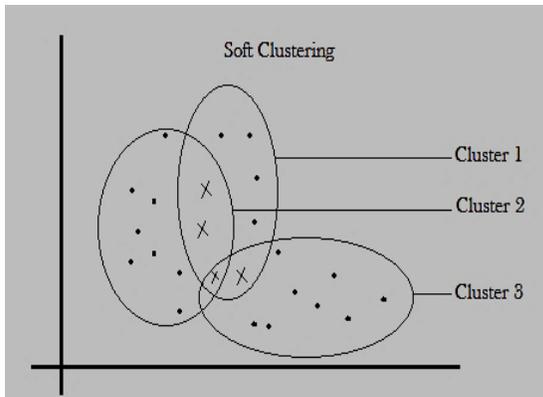


Fig. 9. Fuzzy Cluster Analysis

Data points are marked in above Figure 9 with a black "x" which has maximized membership values below or equal to 0.5. These points have larger degree of uncertainty regarding cluster membership.

To avoid this uncertainty in cluster membership and to adjust the degree of fuzzy overlap in fuzzy clustering, first we run the FCM algorithm for the same clustering task of the user dataset with different values of exponent partition matrix (m) as 1.8, 1.9, 2.0, 2.1 & 2.2 and test which value of exponent (m) is suitable for clustering social network user dataset. Second we set a threshold value to classify each user into the cluster by observing the average maximum value of membership.

13.1 Execute the FCM function with different exponent parameter value by applying following Matlab code.

```
% Specify fuzzy partition matrix exponents.
M = [1.8, 1.9, 2.0, 2.1, 2.2];
for i = 1:5
% Cluster the data.
Set_options = [M(i); % exponent value
100; % max. number of iteration
0.001; % min. amount of improvement
1]; % info display during iteration
options = Set_options;
data = load('fbdataac.dat'); % load data
n_clusters = 6; % no. of cluster
[centers,U,obj_fcn] = fcm(data,n_clusters,options);
end
```

Table 3: shows the overall results.

Exponent value(m)	Max. Number of Iteration	Objective Function Value	Execution Time in Seconds
1.8	40	532.69231	0.878s
1.9	37	463.48279	0.932s
2	36	396.8452	0.828s
2.1	37	338.19008	0.794s
2.2	28	278.1949	0.701s

Table 3: FCM Function Result With Respect To Different Exponent Values

Figure 10 shows the graphical representation of Max. Iteration count with different exponent values

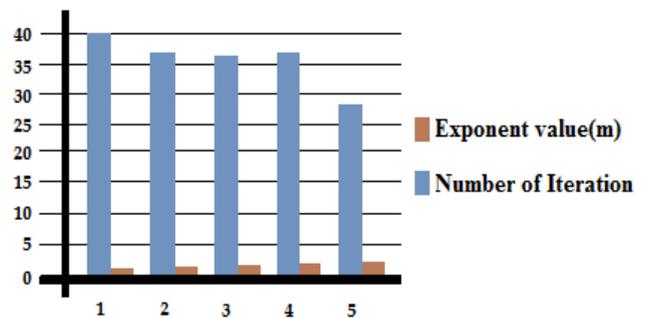


Fig. 10. Max. No. of Iteration for Different Exponent Values

The above results shows that exponent parameter value 2.2 in FCM algorithm is well suitable to perform clustering of given social network users dataset, as it

User	MAG-Ad	ECO-Ad	COM-Ad	SPO-Ad	ENT-Ad	RAN-Ad
1	0.0932	0.0234	0.0132	0.4134	0.4011	0.0557
2	0.2059	0.2000	0.0060	0.0066	0.1062	0.4753
3	0.4000	0.3753	0.2060	0.0059	0.0062	0.0066
4	0.3052	0.3765	0.0192	0.0353	0.2272	0.0366
5	0.2315	0.2601	0.2020	0.0022	0.3022	0.0020
6	0.1960	0.010	0.0060	0.3061	0.4753	0.0066
7	0.4031	0.1724	0.1675	0.0082	0.0081	0.2407
8	0.2604	0.4109	0.2109	0.0573	0.0084	0.0521
9	0.1049	0.2172	0.4009	0.0590	0.1580	0.0600
10	0.0621	0.0254	0.0565	0.4321	0.3234	0.1005

gives minimum execution time, minimum number of total iteration and minimum objective function value.

14. THE AVERAGE MAXIMUM VALUE OF MEMBERSHIP

Now we sat a threshold value to classify each user into the cluster by observing the average maximum value of membership.

```
>> maxU=max (U) ;
    averageMax = mean (maxU)
    averageMax =
    0.3055
```

The average maximum membership value, **averageMax 0.3055**, provides a quantitative description of the overlap.

15. THRESHOLD VALUE

Assume that we set two threshold values $\lambda_1 = 0.4$ and $\lambda_2 = 0.3$. We have found that we can get different results of user classification with different thresholds.

Further, threshold $\lambda_1 = 0.4$ indicates that an individual who holds membership value equal to or greater than 0.4 then he/she is considered as a member of particular advertisement cluster. According to the threshold, $\lambda_1 = 0.3$ the user who holds the value of membership equal

to or greater than 0.3 then he/she is considered as the member of particular advertisement cluster respectively. Moreover, the value of threshold 1 highlight entirely crisp clusters without overlapping and smaller threshold values indicate more overlaps.

By using new exponent parameter (m) value 2.2 in FCM algorithm table 4 shows first 10 user's interest matrix with different online ads categories.

Table 4: User Interest Matrix

Table 5 shows the result of above first 10 users' classification with each advertisement category when threshold $\lambda = 0.4$

User	MAG-Ad	ECO-Ad	COM-Ad	SPO-Ad	ENT-Ad	RAN-Ad
1	0	0	0	1	1	0
2	0	0	0	0	0	1
3	1	0	0	0	0	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0
6	0	0	0	0	1	0
7	1	0	0	0	0	0
8	0	1	0	0	0	0
9	0	0	1	0	0	0
10	0	0	0	1	0	0

Table 5: A Cutting Matrix With $\lambda = 0.4$

Figure 11 shows the graphical representation of degree of fuzzy overlap with threshold value 0.4

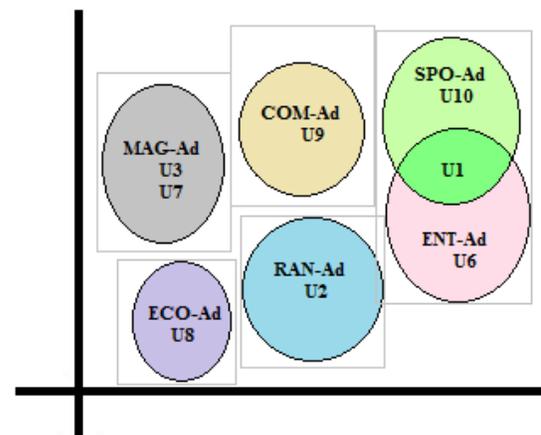


Fig.11 Fuzzy Overlap With $\lambda = 0.4$

A. When $\lambda = 0.4$, the users can be divided into five groups as shown in Figure 11

User Cluster 1: {SPO-Ad, ENT-Ad}



User Cluster 2: {MAG-Ad}
 User Cluster 3: {RAN-Ad}
 User Cluster 4: {COM-Ad}
 User Cluster 5: {ECO-Ad}

Table 6 shows the result of above first 10 users' classification with each advertisement category when threshold $\lambda = 0.3$

User	MAG-Ad	ECO-Ad	COM-Ad	SPO-Ad	ENT-Ad	RAN-Ad
1	0	0	0	1	1	0
2	0	0	0	0	0	1
3	1	1	0	0	0	0
4	1	1	0	0	0	0
5	0	0	0	0	1	0
6	0	0	0	1	1	0
7	1	0	0	0	0	0
8	0	1	0	0	0	0
9	0	0	1	0	0	0
10	0	0	0	1	1	0

Table 6: A Cutting Matrix With $\lambda = 0.3$

Figure 12 shows the graphical representation of degree of fuzzy overlap with threshold value 0.3

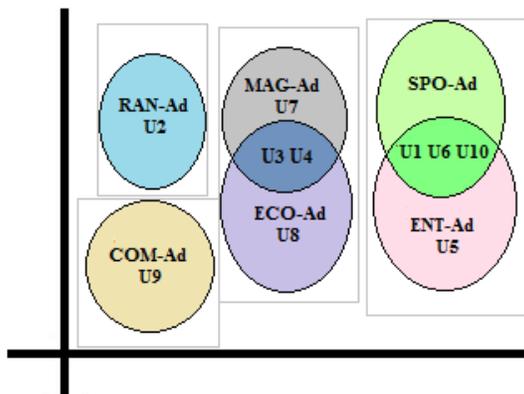


Fig. 12 Fuzzy Overlap With $\lambda = 0.3$

B. When $\lambda = 0.3$, the users can be divided into four groups as shown in Figure 12

User Cluster 1: {SPO-Ad, ENT-Ad}
 User Cluster 2: {MAG-Ad, ECO-Ad}
 User Cluster 3: {RAN-Ad}
 User Cluster 4: {COM-Ad}

A threshold value of 1 indicates completely crisp clusters with no overlapping, and with smaller threshold values indicating more overlap.

16. CONCLUSION

It has been seen that the frequency of the online ads hit and the time for viewing these ads reflects the amount of user and their consideration towards online advertisement. The interest and integration of users towards online advertisement is also seen after research. To determine the viewership of ads, fuzzy classification technique has been used and it is proved to be the effective method to find users with similar interest for online advertisements.

It is observed that once the fuzzy classifications of the user are achieved then it would be easy to facilitate the online marketing by posting the ads by seeing the interest of the users so the success rate for the sales could increase.

REFERENCES

- [1] Tan, Bo, and R. Srikant. "Online advertisement, optimization and stochastic networks." Automatic Control, IEEE Transactions on 57, no. 11 (2012): 2854-2868.
- [2] Moon, Yongma, and Changyun Kwon. "Online advertisement service pricing and an option contract." Electronic Commerce Research and Applications 10, no. 1 (2011): 38-48.
- [3] Ming Yang and Hong Li, "User Analysis Based on Fuzzy Clustering", International Conference on Business Intelligence and Financial Engineering, pp.194 - 196, 2009
- [4] Linda, Ondrej, and Milos Manic. "General type-2 fuzzy c-means algorithm for uncertain fuzzy clustering." Fuzzy Systems, IEEE Transactions on 20, no. 5 (2012): 883-897.
- [5] N. Phillips, "Target markets - Sandpoint marketing and business consulting," in Business Development, Sandpoint Marketing and Business Consulting, 2014. [Online]. Available: <http://sandpointmarketing.com/2014/05/09/target-markets/>. Accessed: Apr. 1, 2016.