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Predicting Facebook Group Relationship

Poonam Rani, M.P.S. Bhatia, Devendra K. Tayal

Abstract: ***Facebook has become the leading social networking site in most countries worldwide. It provides a diverse platform that caters to social, educational and entertainment needs of a user. So, this paper has focused on the Sociocentric Analysis of Facebook. It predicts group relationship of the Facebook social network. The paper proposes to aggregate user's relationships with similar interests and perspectives on the basis of the way in which they provide a reaction to a post on Facebook. The paper has selected the widely used reactions on Facebook posts. The selected reactions on posts are Like, Laugh, Sad, and Wow. In this, a fuzzy pairwise relation between two users in the social network is obtained. For every pair of social actors or users, we have extracted the total number of Facebook posts to which they have reacted in a particular way over a fortnight. The number for each reaction is multiplied with the corresponding weight of the reaction computed by Analytics Hierarchy Process. This fuzzy pairwise relationship is further employed for finding the closely linked group between users by using Ordered Weighted Averaging operator. The devised algorithm has been applied to a sample data of students connected via Facebook social network. The paper has also given several application areas for the proposed work.***

Keywords: ***Social networks, social network analysis, Fuzzy logic, Fuzzy quantifiers, Analytics Hierarchy Process (AHP), Ordered Weighted Averaging (OWA) operator.***

I.INTRODUCTION

A social network is outlined as a network of social interactions among social elements or users. Its users share all types of information at high speeds among themselves. They can stay in touch with each other globally. In this digital age, social media, which creates a social network, is a vital part of every student's life. According to a study conducted in 2011 by Casey and Evans[1], "Social network sites enable students to interact with one another, build a sense of community, develop content, as well as require students to be active in their own learning through participating, thinking, and contributing". Social networking sites and apps like Facebook, Whatsapp, Twitter, Instagram have been paving their way into the life of a common man. Facebook has been found out to be popular among the students. Social network analysis (SNA)[2], [3] refers to analyzing the relationship among individuals or various groups and characterizing the network based on the number of links between the users or group of users. It involves probing the social structure via graph theory and networks. The entities of the network are termed as 'users' while the interactions or relations existing between them are termed as 'links'. SNA is of two types: (i) Sociocentric Analysis (ii) Egocentric Analysis. The 'Sociocentric Analysis' is a technique to analyze and quantify the interactions among a group of users. The 'Egocentric Analysis' is another SNA technique, which focuses on the analysis of individual user node called ego. It analyzes and quantifies the interactions of a single user to all others users in a network. This analysis determines the centrality of the user nodes. This paper aims on Sociocentric SNA How to capture, compare, quantify and analyze these interactions or relationships are the challenging tasks of SNA. We have compared the social networks in our earlier work[4], [5]. Recently also we have also explored one "soft computing based SNA approach"[6] to handle uncertainty in relationship and attributes. These relationships structures are the prime parameters. They need to be mapped and quantified for their outcomes. The quantification process of these valuable relationships in SNA is one of the potential tasks. We have addressed this in our previous work[6], where we have introduced one function for the quantification of the relationship of a network. These relationships in the network are directly quantified on the communication parameter.

This paper has focused on Sociocentric Analysis of Facebook. It presents relationship analysis of the Facebook social network. With 2.271 billion monthly dynamic users on Facebook in the second quarter of 2018 as reported by [7], Facebook has become the leading social networking site in most countries worldwide. It allows sharing of information at a large scale that proves beneficial for every sector of technology users. A user-friendly and appealing interface, the vast multitude of posts, news and media content available each day, entertainment resources, a regular up gradation of features, reporting of inappropriate content and top-notch security make the Facebook community grow multifold. With several thousands of posts that appear in an average user's feed from subscribed pages, the reactions to these posts are highly indicative of their interests and opinions. The various reaction buttons have provided a nuanced view of what catches a user's attention while scrolling through their newsfeed. For calculating the relationship of a group of users of the Facebook social network, the paper has incorporated multiple criteria's.

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*Correspondence Author(s)
Poonam Rani*, Division of Computer Engineering, NSUT, Dwarka, India. Email: poonam.rani.nsit@gmail.com
M.P.S. Bhatia, Division of Computer Engineering, NSUT, Dwarka, India. Email: bhatia.mps@gmail.com
Devendra. K. Tayal, Computer Engineering, IGDTUW University, Delhi, India. Email: dev_tayal2001@yahoo.com

These criteria's are common reactions we get on the posts. The different weights assigned to the Facebook reaction buttons are first used to determine the pairwise fuzzy relations between any two users elements. Then for finding different group potential relationship, these pairwise relationships are combined with OWA[8] operator.

The paper is shaped in seven continuous sections as follows. Section I gives the overview part of social networks, SNA and of the proposed work. Section II discusses the related work with its limitations. Section III discusses the concepts of fuzzy logic, OWA operator and AHP technique. Section IV discusses the detailed proposed method along with the algorithm. Section V illustrates its with an example by taking data from Facebook. Section VI gives some applications area where this proposed work might be fruitful. Finally, Section VII ends the paper by giving some inferences.

II.RELATED WORK

Some authors [9]–[11]have explored this type of work. They have calculated group-relationships between m social users by employing fuzzy pairwise relations between m social elements. For their work, they have explored the OWA - ordered weighted aggregation operator. They have boosted the dimension of analysis from binary to m-size relations. It is advantageous over the classical binary relationship as it preserves more information. But nodes personal characteristics have not been touched. They have taken dummy relationship matrix but not explained from where they have got these fuzzy adjacency relationship values. Neither, they have explored the parameter on which relationship can be calculated. But this paper has explored the communication parameter. That too is on a real social network – Facebook social network. So, the paper has selected the Facebook communication parameter on which relationship can be calculated. For this, the reaction buttons on the Facebook post are selected. The researchers [9]–[11] have used an only a single type of relationship in their work. But, in real life situations, multi-relations exist simultaneous between the social users. In this work multiple relationships have been employed, that depends on multiple reactions of the post. The paper has explored the widely used reactions viz. – Like, Laugh, Sad, and Wow. These reactions on Facebook posts hold different importance in determining the proximity of two users in the social network. For this, the paper has explored AHP[12] technique which is discussed in the next section. The data about the number of like, laugh, sad, wow reacts of a student has been collected from Facebook. This data gives more detailed information because two students reacting to a post, in the same manner, are likely to share similar beliefs about the topic, which gives us a more reliable result.

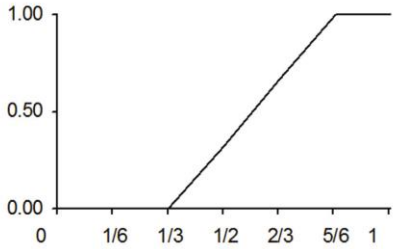
III.CONCEPTS USED-FUZZY LOGIC, OWA OPERATOR AND ANALYTICS HIERARCHY PROCESS

1. FUZZY LOGIC

Fuzzy logic[13], [14] is a multi-valued logic system in which the membership of element is any real value between 0 and 1. It possesses the ability to deal with partially true values, in which the truth-value may be between completely true and completely false, unlike Boolean logic where the variables can hold only completely true or completely false values in the form of 0 and 1. To obtain the mathematical values for representing the fuzzy logic, fuzzy membership functions are used. *Fuzzification* operations are used for mapping mathematical input values into fuzzy membership functions. Fuzzy logic has been proved to be widely useful for several applications as it can control machines and consumer products. It provides acceptable reasoning rather than providing accurate reasoning and thus is widely used in the field of Artificial Intelligence. Two persons may not have the exact same or completely different interests. They may share some common interests and may have different interests in some fields. Therefore a way needs to exist to find out the degree of similarity in the interests that two people in the same network have between them. For this, the paper has used linguistic quantifier discussed below

Linguistic Quantifier

For logical quantifiers like 'all' or 'at least one', it is easy to assign a crisp value to the truths claimed. However in case of linguistic quantifiers like 'most' or 'almost all', a fuzzy-based quantification is necessary. The fuzzy linguistic quantifier F_{LQ} is itself a fuzzy set in [0,1]. For example, a linguistic quantifier such as 'most' can be represented as



$\mu(most)\ x\ =\ 1\ for\ x\ >5/6$

= x/2 - x/6 for ⅓<x<⅚

= 0 otherwise

2. OWA OPERATOR

The OWA[8][5] is an ordered weighted averaging operator is an intelligent operator that facilities a generalized type of mean aggregation operators with some weights. Some members of the OWA class includes the operators - max, arithmetic average, median, and min. It can be used as a schema for aggregating uncertain information directly without knowledge of the weights assigned to this information. Applying the OWA operator on the data obtained from a social network we can figure out the group that has maximum similarities in their interests among the members of the group.

3. ANALYTICS HIERARCHY PROCESS (AHP)

Analytics hierarchy process is a decision-making approach proposed in 1980 by Saaty[12]. It facilitates the process of decision-making using the opinion of an expert in a particular field when multiple criteria for selection are involved and multiple alternatives are available.

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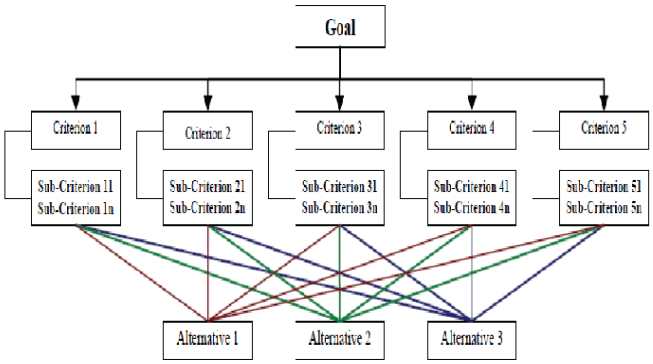
It ranks the alternatives by assigning weights to them. The following steps carry out this process:

a) The problem is formulated into a hierarchy. The goal or objective forms the root. It is decomposed into the criteria at the next level followed by sub-criteria at subsequent levels. Finally, alternatives are placed at the leaf level.



b) For each criterion/sub criteria, a pairwise comparison is performed for the nodes at its next level. The basis of comparison is that criteria.

c) The eigenvector of the pairwise comparison matrix is computed. This leads to the assignment of weights to each edge of the hierarchy.

d) To calculate the priority weight of any alternative, the edge weights leading to it from the goal on a single path are multiplied and then the values for every path are added up.

This technique has multiple applications ranging from defense, supplier selection and resource allocation.

IV.PROPOSED WORK

These days everyone depends heavily on social networking sites for friendship, support, special interests, and knowledge sharing. Facebook is the most used social networking site[7]. So, it has become necessary to study the aspects of a Facebook social network and hence come up with parameters that indicate a potential community with similar interests or learning objectives depending on post reactions. Reacting to Facebook posts has been a recent feature for Facebook SNA. The reaction buttons are designed to let other users know that you acknowledge their comment, post, or picture and indicate a certain responsibility towards it depending on the relationship with him. It is to acknowledge that a mere likeness towards a certain piece of work is not enough and the various nuances of emotions must be explored.

According to Facebook, all reactions to posts at present are ranked equally and there is no measure to indicate the difference intended with the way one reacts to a post on Facebook. This section proposes to extend a modification of this scheme where each reaction is given a different importance and a corresponding weight of each reaction is calculated. This will aid in a better visualization of similarity of interests for two social users by their reactions on a particular Facebook post. As an instance, if a person likes a Facebook post on banning of firecrackers in Delhi while the other reacts angry to the same post, the two cannot be placed on the same page in terms of their perspective. Further, a love react is intended to be a stronger acknowledgment as compared to a like react.

For weighing several criteria, this section extends a pairwise comparison approach that stems from the AHP [12] technique proposed by Saaty. This method concentrates the comparison to only two criteria at a time. The comparison matrix for the reaction buttons on Facebook has been computed intuitively by mutual discussion among a group of frequent users of the website. The following steps will lead us to get a weight for each Facebook reaction.

I. To compute the pairwise comparison matrix: Two reactions are compared pairwise and a relative importance is assigned to them. The importance is assigned using a scale from 1 to 9 proposed by Saaty. According to this method of pairwise importance factor, if a reaction says 'Love' is interpreted to be as important as reaction say 'Wow' in terms of determining the relevance a post holds for an individual, this pair of reaction holds an index of 1 in the pairwise comparison matrix. Similar;y, if reaction, 'love' is much more important in establishing the interests of a social actor than 'like', the index is 9. All values in between can be used to grade the possibilities. The fractions 1/9 to ½ can be used to present a relationship of less importance.

II. The diagonal of the matrix can contain only values of 1. In order for the values to be consistent, the lower half of the matrix is filled with the corresponding fractions of the values in the upper right half.

III. The weights of the individual reactions are calculated. This step requires us to calculate the principal eigenvector of the above-formed matrix, which decides the relative importance of each reaction in the matrix. To compute the principal eigenvector, an approximate method can be applied. Each value in the matrix is divided by the corresponding sum in the column followed by a row-wise mean. These weights are already normalized; their sum is 1.

The parameter for aggregation into a common interest group is the number of posts two people react to similarly. For every pair of social actors, we have extracted the total number of Facebook posts to which they have reacted in a particular way over a fortnight, for instance. The number for each reaction is multiplied with the corresponding weight of the reaction computed previously and the sum over every reaction is calculated. The result is fed into the matrix into the cell, which corresponds, to the social actors taken into account. This procedure is repeated for every pair of social actors and the adjacency matrix is completed.

Once we have the adjacency matrix completed, we can apply the OWA (Ordered Weighted Averaging Aggregation) operator. To evaluate the OWA weights, a method of linguistic quantifiers proposed by Yager [8] has been used. A fuzzy linguistic quantifier denoted by $F_{LQ,}$ is defined by an increasing function, μ_{LQ}: [0, 1] → [0, 1] such that $\mu_{LQ}(0) = 0$ and $\mu_{LQ}(1) = 1$. This is regular if the function is strictly increasing on some interval (c, c¯) ⊆ [0, 1] and is otherwise constant. Further, the weights are optimized to obtain maximal entropy for the above-determined oreness using the analytical method proposed in by Fullér & Majlender[15]. The m-ary fuzzy adjacency relations as proposed by Matteo Brunelli and Michele Fedrizzi OWA operators require a recursive computation of the relations.

These fuzzy adjacency relations indicate the dynamic interactions among the participating social actors and we can effectively decide the social groups that share a common interest. The groups with a high resultant value are capable of exhibiting the potential to work together in educational projects. The algorithm is described as follows:

1. Start
2. Initialize matrix Y, a 2D matrix using the following:
   - Y[i][j] is initialized as 1 when i=j.
   - Otherwise,
     - Y[i][j] = y where y is the importance assigned to reaction i relative to reaction j on scale of 1 to 9.
     - Y[j][i] is initialized as 1/y.
3. Eigenvector V of Y is evaluated where V[i] is the weight assigned to reaction i.
4. Initialize s = Σ V[i]. Modify V[i] as V[i]/s.
5. Now for every pair of social actors A and B, form a vector $_{AB}$
6. T_{AB} is taken as input where each entry $T_{AB}[i]$ is the number of reaction i exchanged between A and B.
7. Normalize the vector by replacing $T_{AB}[i]$ with $(T_{AB}[i]-x)/\{\max(T_{AB}[i])-\min(T_{AB}[i])\}$ where x is the mean calculated by $0.25*\Sigma T_{AB}[i]$.
8. Adjacency matrix R is formed. $R[i][j] = \Sigma_{k=1 \text{ to } 4}(T_{ij}[k]*V[k])$
9. Simultaneously enter R[i][j] into R[j][i] and diagonal entries as 1.
10. Let $m = \lfloor n/2 + 1 \rfloor$ where n = dimension of matrix R.
11. Declare a vector Z to store $\mu_{Rk}(x_i....x_{i+k-1})$ values for k = 3 to m and i = 1 to n-k+1.
12. For k =3 to m do
    - For all k-sized tuples of social actors, $(x_{i1},x_{i2},...,x_{ik})$ where i = 1 to n-k+1
    - Compute $\rho_k(\mu_{Rk-1}(x_{i1},x_{i2},...,x_{ik-1}),...\mu_{Rk-1}(x_{i2},...,x_{ik}))$ using $\Sigma w_j b_j$. Here $b_j = j^{th} \max(a_1,a_2,...,a_m)$ where $a_1,a_2,...,a_m$ represent the operands of OWA operator and w_j is the jth weight.
    - $\mu_{Rk}(x_{i1},x_{i2},...,x_{ik}) = \rho_k(\mu_{Rk-1}(x_{i1},x_{i2},...,x_{ik-1}),...,\mu_{Rk-1}(x_{i1},x_{i2},...,x_{ik}))$ and stored in the vector Z.

It is worth mentioning that the algorithm can be safely adapted to a different analysis with different parameters with varying degrees of importance. The above analysis applies to a group of social actors active on Facebook and with a genuine expression to various posts that appear in their feed. This leads to the relation values being high for groups with common perspectives and interests. Furthermore, common posts appear in the feeds of groups who have followed the same Facebook pages, which provide a stronger ground to our analysis.

V. EXPERIMENTAL WORK

For doing experimental results a short survey is conducted to determine the pairwise importance of reactions on Facebook. The section has selected the widely used reactions on Facebook posts. They are Like, Laugh, Sad, and Wow. The one-to-nine scale has been used since it is most closely resembles our natural ability to distinguish strengths of dominance or preferences between objects. Dr Saaty's Intensity of Importance Scale is shown in table 1. along with the definition of each value.

Table-I:

Intensity of Importance	Definition
1	Equal importance of both parameter
3	Moderate importance of one parameter above other
5	Strong importance of one parameter above other
7	Very strong importance of one parameter above other
9	Extreme importance of one parameter above other
2, 4, 6, 8	Intermediate values
Reciprocals of above nonzero numbers	If one parameter i is given a nonzero value when compared to parameter j, then j has the reciprocal value when compared to i.

The section has taken three different surveys for the calculation of weights of reactions are shown below in table2., table3., and table4., respectively.

Table-II: Survey taker 1 (ST1)

ST1	Like	Laugh	Sad	Wow
Like	1	1/5	1/3	1/5
Laugh	5	1	3	1/3
Sad	3	1/3	1	1/5
Wow	5	3	5	1

Table-III: Survey taker 2 (ST2)

ST2	Like	Laugh	Sad	Wow
Like	1	1/7	1/5	1
Laugh	7	1	3	5
Sad	5	1/3	1	5
Wow	1	1/5	1/5	1

Table- IV: Survey taker 3 (ST3)

ST3	Like	Laugh	Sad	Wow
Like	1	1/5	1/5	1/7
Laugh	5	1	1	1/3
Sad	5	1	1	1/3
Wow	7	3	3	1

To combine the opinions of the three survey takers, the geometric means of the 3 matrixes shown above in table2, table3, and table4 entries are taken. Geometric mean to aggregate the opinions of different survey-takers has been used since arithmetic mean is vulnerable to the scale used in giving opinions. The AHP technique of Saaty adapted for this study uses geometric mean to combine the opinions of multiple experts and we have extended the same approach. The combined values are represented in the matrix Y (table5.) which gives the pairwise relative importance of reactions.

Table-5: Combined pairwise relative importance of reactions

Matrix Y	Like	Laugh	Sad	Wow
Like	1	0.18	0.24	0.31
Laugh	5.49	1	2.06	0.82
Sad	4.21	0.48	1	0.69
Wow	3.23	1.21	1.44	1

Priority weights of reactions are calculated by using this above matrix shown in table5. Several methods of assigning priority weights have been proposed in the literature. Three of them are defined below:

1. **Eigenvector method**[12]

The pairwise comparison matrix A is consistent. The weight vector w = (w1...wn) is shown to be calculated using the eigenvector. In this case, an entry of the matrix aij = wi/wj. and Aw = λw where λ is the principal eigenvalue of the matrix A. If A is an inconsistent matrix, then eigenvector does not give priority weights.

2. **Data Envelopment Analysis**[16]

This method functions on the objective to maximize the efficiency of decision-making units. Each row of the pairwise comparison matrix is treated as a decision unit that converts multiple inputs into multiple outputs. Each column as the output and assumes dummy inputs. A linear programming model is solved for each decision-making unit and the priority weights are obtained. DEA method gives the accurate weights if the comparison matrix is perfectly consistent.

3. **Logarithmic Least Squares Method**

This method assigns priority by computing the normalized geometric mean of each row.

All the three methods discussed above give realistic priority weights when the comparison matrix is consistent. In the AHP technique proposed by Saaty, Eigenvector method has been used and the section has explored it for the experimental study. The formula used is as follows where A is any matrix, λ is the scalar quantity known as the eigenvalue and v is the corresponding eigenvector:

$$A \cdot v - \lambda \cdot v = 0 \quad (1)$$
$$A \cdot v - \lambda \cdot I \cdot v = 0 \quad (2)$$
$$(A - \lambda \cdot I) \cdot v = 0 \quad (3)$$

Since the system is consistent, the characteristic equation is formed by determinant (A - λ·I) = 0.

For the pairwise comparison matrix, on substituting determinant (Y - λ.I) = 0, we get

$$\begin{vmatrix} 1-\lambda & 9/50 & 6/25 & 31/100 \\ 549/100 & 1-\lambda & 103/50 & 41/50 \\ 421/100 & 12/25 & 1-\lambda & 69/100 \\ 323/100 & 121/100 & 36/25 & 1-\lambda \end{vmatrix} = 0$$

The characteristic polynomial formed is:

$$\lambda^4 - 4 * \lambda^3 + \frac{51}{2000} * \lambda^2 - 1.48173 * \lambda - \frac{6269393}{50000000} = 0 \quad (4)$$

Solving for λ, we get λ to be real and positive as 4.084

The maximum eigenvalue is found and normalized eigenvector is calculated corresponding to this eigenvalue by substituting in equation (3). The elements of this normalized eigenvector give the weights of criteria. The eigenvector of matrix Y is calculated using the formula. The eigenvalue for the matrix, which gives maximum eigenvector, is λ = 4.084 and the corresponding eigenvector is given below in table6.

Table-6:

Like	0.22
Laugh	1.12
Sad	0.70
Wow	1

The normalized eigenvector gives the priority weights of the reactions are given below in table7. Normalization is performed by dividing each value by the sum of all values in the vector.

Table-7:

Like	0.07
Laugh	0.37
Sad	0.23
Wow	0.33

For experiment results the section has applied the proposed work to six students on Facebook social network FS_1, FS_2, FS_3, FS_4, FS_5, and FS_6. The data about the number of like, laugh, sad, wow reacts of these 6 students has been collected from Facebook. Consider matrix A consisting the number of posts on which FS_1 reacted similarly as the other social actors FS_2, FS_3, FS_4, FS_5, and FS_6 is shown in table8.

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The posts can be audios, videos or textual information that appear in the student's newsfeed. They can be from the pages the student has subscribed to or posted by a friend. Here $P^{like}_{FS_1FS_2}$ denotes the number of posts to which students FS_1 and FS_2 gave the reaction like. Similarly, $P^{laugh}_{FS_1FS_2}$ denotes the number of posts to which students FS_1 and FS_2 gave the reaction laugh. This can be generalized as:

$$P^{k}_{FS_iFS_j} = \text{number of posts to which students } FS_i \text{ and } FS_i \text{ gave the reaction } k \text{ where } k \text{ can be like, laugh, sad or wow.}$$

The vector $P_{FS_iFS_j}$ gives the number of posts on which the students' S_i and S_j gave the same reaction.

Table-8:

	Like	Laugh	Sad	Wow
$P_{FS_1FS_2}$	4	7	8	2
$P_{FS_1FS_3}$	1	3	4	9
$P_{FS_1FS_4}$	3	5	6	7
$P_{FS_1FS_5}$	1	2	5	4
$P_{FS_1FS_6}$	8	2	1	1

Consider matrix B consisting the number of posts on which FS_2 reacted similarly as the other social actors FS_3, FS_4, FS_5, and FS_6 is shown in table9.

Table-9:

	Like	Laugh	Sad	Wow
$P_{FS_2FS_3}$	3	2	5	6
$P_{FS_2FS_4}$	1	4	9	2
$P_{FS_2FS_5}$	4	4	7	8
$P_{FS_2FS_6}$	2	1	4	3

Consider matrix C consisting the number of posts on which FS_3 reacted similarly as the other social actors FS_4, FS_5, and FS_6 is shown in table10.

Table-10:

	Like	Laugh	Sad	Wow
$P_{FS_3FS_4}$	3	6	7	1
$P_{FS_3FS_5}$	1	2	4	8
$P_{FS_3FS_6}$	3	3	6	6

Consider matrix D consisting the number of posts on which S_4 reacted similarly as the other social actors S_5, and S_6 is shown in table11.

Table-11:

	Like	Laugh	Sad	Wow
$P_{FS_4FS_5}$	5	8	7	1
$P_{FS_4FS_6}$	3	5	7	9

Consider matrix D consisting the number of posts on which S_5 reacted similarly as the other social actors S_6 is shown in table12.

Table-12:

	Like	Laugh	Sad	Wow
$P_{FS_5FS_6}$	2	4	7	3

Now to get the pairwise relationship between two social actors, we take the sum of the product of the number of reactions stored in the corresponding vector and the weight of the reaction. Here $P_{ij}(k)$ denotes the number of posts to which students si and sj gave the reaction k. It is multiplied by w(k) which is the corresponding weight of the reaction k found above.

$$R_{ij} = \Sigma_{k=1to4} P_{ij}(k)*w(k)$$

For example: To get the pairwise relation between FS_1 and FS_2, ($R_{FS_1FS_2}$); we use: 4*0.07 + 7*0.37 + 8*0.23 + 2*0.33 = 5.37 followed by normalisation by dividing by the maximum values.

Therefore, the matrix R obtained is the following.

Table-13:

R	FS_1	FS_2	FS_3	FS_4	FS_5	FS_6
FS_1	1	0.29	0.26	0.46	0.33	0.38
FS_2	0.29	1	0.17	0.27	0.24	0.51
FS_3	0.26	0.17	1	0.40	0.30	0.50
FS_4	0.46	0.27	0.40	1	0.25	0.36
FS_5	0.33	0.24	0.30	0.25	1	0.25
FS_6	0.38	0.51	0.50	0.36	0.25	1

OWA Operator

An OWA operator of dimension n is a mapping F: RR_n that has an associated collection of weights W = $[w_1 \ldots w_n]$ lying in the unit interval and summing to one.

$F(a_1 \ldots a_n) = \sum_{j=1 \text{ to } n} w_j b_j$ where b_j is the jth largest of the a_i.

- For calculating the weights w_j, consider a typical quantifier 'more than 25%' given by Q(x)
  $\mu_{FQ}(x) = \{0 \text{ for } 0 \leq i/n \leq 0.25$
  $(i/n - 0.25) / 0.75 \text{ otherwise}\}$
- The weights are calculated using the formula $w_k = Q(k/n) - Q(k-1/n)$.

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Applying the above equation for n = 6 gives the weights as $w_1 = 0$, $w_2 = 0.11$, $w_3 = 0.223$, $w_4 = 0.3325$, $w_5 = 0.4452$, $w_6 = 0.5542$

- Further optimizing the weights to obtain maximal entropy for the above determined oreness using we get, $w_1 = 0.129$, $w_6 = 0.2095$, $w_2 = 0.1421$, $w_3 = 0.1566$, $w_4 = 0.1725$, $w_5 = 0.1901$

Maximal entropy is aimed for because we want to maximize the dispersion so that we do not obtain biased weights, which can reduce the OWA operator to min, max or simple average. It can be observed that w_i is monotonic and $\Sigma w_i = 1$.

Now applying the OWA operator recursively, we get:

Table-14:

Size	Possible combinations	Aggregation Value	Max. Value
3	$FS_1FS_2FS_3$,$FS_1FS_2FS_4$, $FS_1FS_2FS_5$,$FS_1FS_2FS_6$, $FS_1FS_3FS_4$,$FS_1FS_3FS_5$, $FS_1FS_3FS_6$,$FS_1FS_4FS_5$, $FS_1FS_4FS_6$,$FS_1FS_5FS_6$, $FS_2FS_3FS_4$,$FS_2FS_3FS_5$, $FS_2FS_3FS_6$,$FS_2FS_4FS_5$, $FS_2FS_4FS_6$,$FS_2FS_5FS_6$, $FS_3FS_4FS_5$,$FS_3FS_4FS_6$, $FS_3FS_5FS_6$,$FS_4FS_5FS_6$	0.14, 0.17, 0.13, 0.19, 0.15, 0.127, 0.18, 0.137, 0.196, 0.15, 0.141, 0.11, 0.172, 0.116, 0.143, 0.182, 0.154, 0.13, 0.165, 0.132	0.196 (FS_1, FS_4, FS_6)
4	$FS_1FS_2FS_3FS_4$, $FS_1FS_2FS_3FS_5$, $FS_1FS_2FS_3FS_6$, $FS_1FS_2FS_4FS_5$, $FS_1FS_2FS_4FS_6$, $FS_1FS_2FS_5FS_6$, $FS_1FS_3FS_4FS_5$, $FS_1FS_3FS_4FS_6$, $FS_1FS_3FS_5FS_6$, $FS_1FS_4FS_5FS_6$, $FS_2FS_3FS_4FS_5$, $FS_2FS_3FS_4FS_6$, $FS_2FS_4FS_5FS_6$, $FS_2FS_3FS_5FS_6$, $FS_3FS_4FS_5FS_6$	0.323, 0.265, 0.464, 0.192, 0.193, 0.223, 0.322, 0.432, 0.212, 0.123, 0.456, 0.122, 0.145, 0.355, 0.234	0.464 (FS_1, FS_2, FS_3, FS_6)
5	$FS_1FS_2FS_3FS_4FS_5$, $FS_1FS_2FS_3FS_4FS_6$, $FS_1FS_2FS_3FS_5FS_6$, $FS_1FS_2FS_4FS_5FS_6$, $FS_1FS_3FS_4FS_5FS_6$, $FS_2FS_3FS_4FS_5FS_6$	0.543, 0.554, 0.435, 0.334, 0.245, 0.385	0.554 (FS_1, FS_2, FS_3, FS_4, FS_6)

It is observed that as the size of the groups increases, the relationship between the participating members becomes stronger. This can be attributed to the belief that when the size of the group is large, there are more chances of colliding interests in terms of the number of Facebook posts to which the students react similarly. Since every reaction is assigned a worth, larger groups are preferred.

VI.APPLICATION AREAS

In future work, the paper is going to explore this work on following applications areas given below:

Recommendation System: It can use the proposed algorithm for group recommendations. People with similar interests are recommended to form a group. The evaluation criteria can be set according to the requirement. The proposed algorithm evaluates the degrees of closeness in a group using which potential groups for projects and meet can be formed.

To identify criminal activities: People who are recognized to share interests with an identified criminal can be the part of his gang that performs criminal activities in the neighbourhood.

Course suggestions: Since the algorithm calculates the pairwise relations as well, it can be used to suggest courses to a student sharing similar interests with another student.

VII.CONCLUSION

Our analysis estimates how much a group of students share in common and thereby determines how likely they are to interact with each other. The proposed parameter is similarity of reaction to a particular Facebook post to determine the social actors sharing common interests. The paper measures the strength of a group of six students depending on their interactions. It has also calculated the potential group out of each group with all sizes three, four and five respectively. In the next work, various possible applications will be explored in detail.

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AUTHORS' PROFILES

Mrs. Poonam Rani is a assistant professor in Division of Computer Engineering, NSUT, New Delhi, India. She is doing her Ph.D. under Delhi University, India. Her research interests are Social networks, Theory of automaton, and fuzzy logics.

Prof. M.P.S. Bhatia is a professor in Division of Computer Engineering, NSUT. Presently he is guiding various Ph.D. students. His main research areas are Data mining, Big Data, Machine learning, Social networks. He has good publication list in good national and International Journals.

Prof. Devendra K. Tayal is a professor in department of Computer Engineering, IGDTUW, India. Presently he is guiding various Ph.D. students. His research areas are Data Mining, Database Management Systems, Social network, Fuzzy Logic and Intelligent Systems. He has good publication list in good national and International Journals.