IDENTIFICATION OF FACTION GROUPS AND LEADERS IN WEB BASED INTELLIGENT ARGUMENTATION SYSTEM FOR COLLABORATIVE DECISION SUPPORT

ABSTRACT
Argumentation is an important and critical process in a collaborative decision making environment. Several argumentation frameworks and systems have been proposed for collaborative decision making earlier. However, limited decision support is provided to stakeholders. In an argumentation process, stakeholders tend to form groups, called faction groups based on their opinions and exchange of arguments. Each faction group is usually led by a faction leader in the group. Identification of faction groups and leaders in argumentation becomes an important challenge which has not been addressed adequately in the past. The faction assessment in argumentation provides the decision maker with more information about faction groups and their opinions towards the given issue and it helps the decision maker with logical and analytical competency to assess and analyze post-decision effects on each faction group and faction leaders, and make rational decisions. In this paper, we present a framework for identifying faction groups and faction leaders in an argumentation process using the K-means clustering algorithm. It is evaluated using a data set: an argumentation tree developed by a group of 24 stakeholders in an argumentation process using our web-based intelligent argumentation system for collaborative decision support. The experimental results show that the framework works effectively for faction assessment.

1. INTRODUCTION
The argumentation process allows the stakeholders to debate with peers and to closely deliberate the alternative solutions for the given issue. The stakeholders in the decision making group have their own choice of support for alternative solutions for the decision making. In the process, stakeholders with similar opinions tend to get closer by supporting among themselves through the arguments and attacking stakeholders who have a different opinion about the issue. Through their arguments, the decision making group develops different factions among them. A group of stakeholders who share a similar opinion for a given issue and exchange arguments with other stakeholders to make their opinion as the decision is called a faction group. The stakeholder in a faction group who receives the highest support from their faction group is called the faction leader of that group. A normal person with sound logical competency can identify the formation of groups, and group leaders in the argumentation and debate process. The process of identifying the faction groups and faction leaders is new to the argumentation systems and collaborative decision support paradigms. This information could assist the decision maker in making more in-depth analysis of the alternatives of the issue and taking more appropriate decisions.

For example, in a software organization the project manager posts a software product testing related issue and all the stakeholders in the organization including the financial department stakeholders participate in the argumentation process. If the decision maker has the faction assessment information, then the decision maker could analyze the opinion of a faction group which has majority of software developers and testers along with the opinion of a faction which has finance department managers and employees. This information could help the decision maker in taking more appropriate decisions, and he/she might go with the opinion of faction group which has software developers and testers. The Web-based intelligent argumentation system provides stakeholders to post their arguments supporting and attacking alternatives and arguments posted by other stakeholders. The framework captures the total support and the total attack of a stakeholder towards each alternative through the arguments provided by them, and computes the opinion of every stakeholder in the group towards each alternative solution, and based on the similarity in the opinion of stakeholders, they are classified in to different faction groups and the interactions among the stakeholders in the group are captured through their arguments. These interactions allow the system to identify the faction leader in a faction, a stakeholder who receives the highest favorability from his faction group through the arguments is the faction leader of that group, and the favorability is computed as the sum of total support received and the total attack received from rest of the group through their arguments. Although there are faction groups within a faction group, intra-group factionism is a part of our future work. The participants in the decision making group hail from different backgrounds, cultures with different perspectives towards the problem domain and during the argumentation process the conflicts among the participants are inevitable, and these conflicts among the stakeholders are through their arguments. Each stakeholder believes in their decision and when working collaboratively on an issue, the group can accurately sense the problem with different perspectives and they could correlate the
post-decision effects with their personal and professional requirements, and based on that they support and attack different alternatives through their arguments. The following section in this paper presents the related research work and literature, section 3 briefly presents the intelligent argumentation system, section 4 presents the framework for faction assessment and section 5 evaluates the framework and section 6 concludes the paper.

2. RELATED WORK

2.1. Social Impact Theory
The dynamic social impact theory proposed by Latane is a highly influential theory which presents the effects of other stakeholders on an individual stakeholder in a group during their interactions [1]. In dynamic social impact theory, Latane proposed three different principles: (1) the social impact or influence received by a target stakeholder in a group is because of the social forces i.e., other stakeholders in the group, (2) as the strength of the social forces increases, the influence also increases and (3) when more stakeholders join the individual targeted stakeholder, the total influence received by this newly formed target group is diluted among the stakeholders in the group; hence, the impact is reduced [1]. The proposed theory also applies for a group of stakeholders in the debate process and the argumentation process where the influence is presented through the arguments and the arguments’ strength. In the extended research work of Latane, he proposed that the groups formed are very dynamic by nature; they keep changing throughout the discussion process since the stakeholders change their opinions when exchanging arguments [5]. As the arguments among the stakeholders are exchanged, the opinions of the stakeholders might change, and stakeholders with similar opinions form into groups. Consolidation, clustering, correlation and continuing diversity are the four group-level phenomena [2][3][4] that a group holds. The dynamic social impact theory states that stakeholders form groups, and these groups tend to polarize on issues based on their opinions. The stakeholders in these groups are the ones with similar opinions. We believe that the social dynamics exists in the argumentation systems, and the dynamic social impact theory holds for the argumentation systems.

2.2. Argumentation Systems
The argumentation systems support the stakeholders to understand the rational and critical thinking and to organize the posts in the argumentation tree which helps in comprehending the information. The theories of argumentation systems have been widely accepted and used for multi-agent communication, natural language processing, user modeling etc [6]. Because of the wide applications of the argumentation systems in various fields and domains for collaborative work support, different systems have been proposed by scientists and they are built upon various formal and informal argumentation models. The great philosopher Stephen Toulmin has proposed an informal model of argumentation system and many argumentation systems in the present day follow the Toulmin’s influential argumentation model.

Araucaria is one of those argumentation systems that support stakeholders in building the argument tree, analysis and representation of the arguments [6]. The Araucaria argumentation system is built upon the rhetorical structure theory. The system supports various argumentation schemes, and the user has the freedom to select the argumentation scheme of their own choice. The stakeholders should have prior knowledge about the argumentation schemes and they should know which scheme is more appropriate for them. This software is mainly used for students in the educational system. Argumentative [7] allows the stakeholders to post their issues under which they can post their premises, reasons and objections. Every node in the tree has a comment attached to it, which describes the meta-data of that node, and presents the author of the element, date, etc. This is open source software which follows the informal argumentation models, and it has great visualization ability. Since this system is not a weighted argumentation system, the decision support provided by the system could be limited. Compendium [16] is an argumentation system inspired from the IBIS system, and the IBIS system follows the Toulmin’s informal argumentation system. Truthmapping [15] and Debategraph [14] are other systems that support argumentation and debating, which are available for free over the Web. All these systems follow a tree structure for the representation of the information. Since they are not weighted argumentation systems, it would be difficult to provide decision support assistance, and all these systems cannot perform intelligent analysis of the arguments. They only allow exchanging the arguments. These systems are more advanced than blogs and forums for supporting group discussions. Faction assessment might not be possible in Webblogs, political blogs, because the participants here do not have the opportunity to express their posts quantitatively. It might be difficult to understand the association or relationship between the posts. There are several other argumentation systems [8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, and 19], and some of them are open source. Although faction identification is new to the argumentation systems, several scientists are working in the area of community detection in social networks [23].

3. INTELLIGENT ARGUMENTATION SYSTEM

3.1. Components of argumentation tree
The intelligent argumentation system allows the stakeholders to interact through their arguments over the Web. Stakeholders can post their issues in their project and post their alternative positions under the node issue in the argumentation tree, see Figure 1. A stakeholder can post arguments supporting or attacking alternative positions or other arguments in the argumentation tree. Every argument carries a weight which represents its association with its parent node. The argument strength ranges from -1 to +1 which is explicitly provided by the stakeholder while posting the argument. A negative strength
indicates that the argument is attacking its’ parent argument, an argument with positive strength signifies that the argument is supporting its parent node, and argument strength with 0 signifies indecisiveness. The stakeholders are responsible for constructing the argumentation tree, and they have to provide the strength of the argument explicitly while posting an argument. Figure 1 illustrates a snapshot of the intelligent argumentation system.

3.2. Decision support through arguments
The stakeholders in the argumentation process hail from different backgrounds, cultures, and with different scale of experience and hence conflicts are inevitable. All the arguments in the argumentation tree are reduced to one level in the tree based on the fuzzy inference rules. Once all the arguments of a tree are directly connected to an alternative, the favorability factor of an alternative is derived through the arguments.

Every participant in the decision making group has a priority within the group over other participants, and this priority value ranges from 0.1 to 1.0. The lower the priority value is, the lower the priority of a stakeholder in the group. The higher value signifies the higher priority of a stakeholder. The intelligent argumentation system uses the priority of a stakeholder to reassess the weight of arguments posted by that stakeholder. The reassessment of the weights is based on the argument weight assessment fuzzy inference engine developed using the fuzzy heuristic and fuzzy inference rules [20] [21]. The detection and resolution of the conflicts is based on a set of fuzzy heuristic rules and fuzzy inference engine. The good side of having conflicts among stakeholders is that it refines the opinions of the stakeholders by exposing them to different viewpoints.

In the case of product design, conflicts among stakeholders may result in an improved architecture. The fuzzy inference engine takes crisp values as inputs, and based on the fuzzy membership functions, these inputs undergo fuzzification process. The output of the fuzzification process gives input to the fuzzy inference engine, where it is directly connected to fuzzy rule base called fuzzy associative matrix. Based on the rules of the fuzzy associative matrix, new values are returned to the defuzzification process. In the defuzzification process, the obtained inputs are converted to crisp outputs.

3.3. Decision support through MCDM
Multi criteria decision making (MCDM) assists participants in analyzing each alternative with different criteria, and eases in the decision making procedures. The computation of the performance scores in the decision matrix for MCDM is a challenging problem. The argumentation process can quantify the numerical values of the performance scores. We have addressed this challenge by introducing an intelligent computational approach [5] to compute the performance scores in a decision matrix. In MCDM, each criterion is given a numerical weight based on the importance of the criteria. We have used the Analytic Hierarchy Process to get the weights of the criteria. Once the weights are obtained, weighted summation is carried out with the performance scores to get the favorability factor of the alternatives, and hence the intelligent argumentation system has the ability to support MCDM.

4. FRAMEWORK FOR FACTION ASSESSMENT

4.1. Identification of faction groups
The intelligent argumentation system allows the stakeholders to post their issues, alternative solutions, exchange and support their arguments by posting evidences. With the participation of the stakeholders, the argumentation tree is built. In the argumentation process, the stakeholders’ exchange arguments in the tree and the height of the argumentation tree evolves during the process. Once the argumentation process is over, the intelligent argumentation system reduces all the arguments to one level such that all the arguments now are directly associated with the respective alternative.

Once all the arguments are reduced, the strength values of all the arguments posted by a stakeholder under an alternative
are accumulated, and the favorability of a stakeholder for that alternative is captured. This process is carried out for all the stakeholders under all the alternatives. Once the data is collected from the argumentation tree, the data is normalized to keep the consistency in the data. Now we have the favorability factor of each stakeholder for each alternative. Hence, we have the opinion of the stakeholders for the given issue with respect to the alternatives. The favorability factor represented by a numerical value represents the sum of total support and total attack of a stakeholder towards an alternative.

The following formula is used for normalizing the data using the min-max normalization technique, min A, and max A are the minimum and the maximum values in the data collected from the argumentation tree for an alternative i.e., attribute, and new_min A, new_max A is the new range for the data provided.

\[
v' = \frac{v - \text{min } A}{\text{max } A - \text{min } A} (\text{new } \text{max } A - \text{new } \text{min } A) + \text{new } \text{min } A
\]

Since we have the opinion of each stakeholder, the K-means clustering algorithm could be used to group the stakeholders with the similar opinions, the favorability factor of each stakeholder towards all the alternatives is taken as a vector and the Euclidean distance is used for similarity measurement. In K-means clustering algorithm, ‘K’ represents the number of clusters which is provided as input along with the argumentation data. The K-means algorithm randomly considers ‘K’ points in the given range as the initial centroids of the clusters [22]. After each iteration, the data are compared with these ‘K’ centroids using the Euclidean distance. Each data point is assigned to a cluster whose centroid is closest to it. At the end of each iteration, the centroid is updated. This process is carried out for all the data and for several iterations until the convergence is achieved, which can be evaluated by the mean square error within the cluster.

Once the convergence is achieved, the algorithm stops and produces ‘K’ number of clusters, where each cluster has data points that are as close as possible, and these data points have as much difference as possible with data points in other clusters. Each cluster produced by this algorithm is considered as a faction group, since they are clustered based on the similarity of their opinion. The centroid of each cluster represents the opinion of the cluster. The value of ‘K’ should be provided by the decision maker as input to the algorithm, and it is up to the decision maker to provide the ‘K’ value, as how many groups he/she would like to see among the stakeholders. The following Euclidean distance formula is used for computing the similarity measurement among the participants. X1, X2, and X3 represent the favorability factors for alternative 1, 2 and 3 by stakeholder X, and Y1, Y2, Y3 represents the favorability factors for alternative 1, 2 and 3 by stakeholder Y, this derives the similarity measurement among the stakeholders X and Y.

\[
d(X, Y) = \sqrt{(X1 - Y1)^2 + (X2 - Y2)^2 + (X3 - Y3)^2}
\]

4.2. Identification of faction leaders

After the system produces the faction groups, the interactions among the faction group members are captured through the arguments. The sum of total support and total attack of the arguments posted by a stakeholder towards other stakeholder in the faction group is computed which provides the relationship among the stakeholders. The stakeholder with the highest support from his/her faction group is declared as the faction leader of that faction group. In some cases, there may be a tie among the stakeholders in the same faction group for leadership, and in this case, we would select a faction leader randomly among the stakeholders who have tie for the leadership position.

5. EMPIRICAL EVALUATION

5.1. Objective

Our objective in this empirical evaluation is to identify the faction groups who share similar opinions and faction leaders in the group. We have conducted an experiment with a group size of 24 stakeholders who were recruited from the Software Engineering class. The data in the experiments presented below are from the real discussions. We would like to evaluate our framework by running it through the argumentation tree built by the group. We have used WEKA [24], data mining software for these experiments.

5.2. Case Study Background

Software metrics adoption is an important concern, and its’ application to the projects depends on various factors such as size of the organization, size of software project, etc. The empirical study is carried out on a case study based on the selection of software metrics for organizations. The decision issue is about the selection of software metrics program for a large scale organization, and under this issue, the 24 stakeholders have exchanged 220 arguments. No metrics program, light weight metrics program, and comprehensive metrics program are the three different alternative solutions provided. -13.910, -2.398, and 18.868 are the favorability factor for each alternatives respectively produced by the intelligent argumentation system.

5.3. Issue 1 – Large Scale Organizations

The 24 stakeholders have built the argumentation tree for this issue with the size of 220 arguments over a period of 1 week. After the argumentation process, the arguments in the argumentation tree were reduced to one level such that all the arguments are now directly associated with the positions based on the fuzzy inference rules [20] [21]. The total contribution made by each stakeholder towards the alternative position is captured through the argument weights. These weights are summed up to find the opinion of the stakeholder towards the issue under this alternative. The opinion of all the stakeholders were computed for the three alternative positions for this issue, and the accumulated data was normalized using min-max normalization method. The K-means clustering algorithm was
run on the data for 4 clusters. The algorithm produced 4 clusters and each cluster centroid is presented in Table I.

TABLE I. CENTROIDS OF CLUSTERS

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Cluster 0</th>
<th>Cluster 1</th>
<th>Cluster 2</th>
<th>Cluster 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Position 1</td>
<td>0.6066</td>
<td>-0.3497</td>
<td>0.6929</td>
<td>-0.335</td>
</tr>
<tr>
<td>Position 2</td>
<td>0.0097</td>
<td>-0.7602</td>
<td>-0.0364</td>
<td>0.4902</td>
</tr>
<tr>
<td>Position 3</td>
<td>-0.2335</td>
<td>-0.5813</td>
<td>-0.5864</td>
<td>0.3699</td>
</tr>
</tbody>
</table>

1) **Faction groups** - Each cluster produced by the algorithm represents a faction group among the stakeholders, and the centroid of the cluster represents their opinions towards the given issue in terms of the position favorability value. The positive value of position favorability represents the support and the negative represents the attack. Figure 3 presents the four clusters produced by the K-means clustering algorithm. Cluster 0 consists of 7 stakeholders, and the centroid of the cluster (0.6066, 0.0097, -0.2335) signifies that the stakeholders in this faction group support position 1 and position 2 and they are against the position 3. The cluster 1 consists of 3 stakeholders who attack all the three alternative positions. Cluster 2 consists of 9 stakeholders who strongly support position 1 but attack position 2 and position 3. Cluster 3 consists of 5 stakeholders who support position 2 and 3 but attack position 1. These results show that stakeholders in cluster 0 and cluster 3 share contrasting opinions. This enables the decision maker to understand the support and attack of each faction group and to make more appropriate decisions.

2) **Faction leaders** - Every faction group is lead by a leader, and in our system, a stakeholder who receives the highest support from the group through arguments is the leader of the group. Table II presents the stakeholders in each faction group. After the evaluation of each stakeholder’s support within the group from the other stakeholders in the group, the faction leaders are S5, S19, S2 and S17 in faction 0, 1, 2 and 3 respectively.

![Figure 3. Four clusters produced by the K-means clustering algorithm](image)

### 5.4. Analysis and Observations

The proposed framework was evaluated successfully, and the intelligent argumentation system has identified the faction groups and faction leaders successfully. In the evaluation phase, we came across some factions who do not support any of the alternatives, but in fact those groups attack all the alternatives. Sometimes we come across this kind of situations in real life scenarios where in the decision making group some people do not support any alternatives and attack all the alternatives. Another important observation made during the experiment was that although the stakeholders within a faction group share similar opinion, they attack one another through their arguments. Although the stakeholders share the same opinion, there is a varied level of support and attack towards the alternatives. So we can use hierarchy clustering techniques to identify both inter-group and intra-group factions. Although the same set of stakeholders have participated in all the three issues in the experiment, the stakeholders in these faction groups were never the same, and the stakeholders in the group were changing from issue to issue. Stakeholders in groups are usually influenced through the arguments of other stakeholders and may change their opinions [5].

### 6. CONCLUSIONS

Identification of faction groups and leaders in a decision making group can assist in making an informative decision. It could help a decision maker to identify influencing participants in faction groups in an argumentation process. In addition, it could provide informative feedback to the stakeholders in the argumentation process. Detection of outlier opinions, their factions, their faction leaders in argumentation using outlier detection techniques are a part of our future work.

### 7. ACKNOWLEDGMENTS

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### 8. REFERENCES


[16] Compendium, compendium.open.ac.uk/institute/, 12/3/2011 (access date)


