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Assessing Impact of Social Network on Formation of Opinions in Integrated Intelligent Argumentation with Social Network

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Abstract— **Cyber-Argumentation platforms facilitate large-scale online deliberations with appropriate structures and features to capture decision rationale and collective intelligence. Research advances have been made on its model, algorithms, and applications. Social networking has significant impacts on the formation and evolution of individual and collective opinions in cyber-argumentation. Social connections in social networking aspects like friends and follows relationships among users in cyber argumentation can reveal the patterns, shifts, and true relationships between the users in a discourse that influence collective decision-making process. However, the impacts of social networks on the formation and evolution of collective opinions in cyber-argumentation have not been studied systematically. There are currently no methods for assessing the impacts of social networks on the formation of collective opinions in cyber-argumentation. In this research, we propose a method to quantify the impact of social networking on cyber-argumentation. We investigate three types of impacts: directional impact, mutual impact, and social group impact. These represents the contribution of an individual user or group to the formation of a collective opinion for a specific issue in intelligent cyber argumentation system, a platform for cyber argumentation with social networking we have developed. These different measures help quantify what a person's social group thinks about his or her opinions and their impacts on their arguments. Finally, using these impact measures, we developed an algorithm to detect the pseudo-supporters of an individual in an argumentation network. The proposed methods and algorithm have been implemented based on our intelligent cyber-argumentation system with social networking. They have been studied empirically which shows that our quantification methods and algorithm enable the quantitative assessment of social connections and the detection of pseudo-supporters in cyber-argumentation.**

Keywords—Cyber-Argumentation, Social Network Impact, Argumentation Opinion Analysis, Argumentation Group Analysis, Social Argumentation Network, Social Argumentation Analysis, Pseudo-Supporters.

I. Introduction

In today's interconnected world, most of the decision-making is driven by the massive online activity of users. These online deliberations are made possible by several social media platforms like emails, chat rooms, discussion forums, social networking websites, and so on. With this immense user participation in any discussion, we will harvest many benefits, such as crowd wisdom (which refers to group judgments being stronger than individuals) and collective intelligence (which represents group intelligence being far greater than individuals). To capture and evaluate this crowd wisdom and collective intelligence, argumentation frameworks institute specific structures explicitly for massive online deliberation. Cyber-Argumentation experts have created these specialized argumentation platforms to efficiently support and evaluate online discourse. These platforms frequently use theoretical argumentation frameworks that encourage better reasoning and provide insightful debate analysis.

Relationships in social networks can be friendship, influence, trust, affection, or, conversely, dislike, conflict, or many other things. They can be binary, symmetric, asymmetric, or multimode. Most social networks now have either symmetric, asymmetric, or both relations. A symmetric relationship is primitively a two-way relationship. They are represented as an undirected graph. One example is the "friend" relationship. On the other hand, an asymmetric relation is one way represented by the directed graph. The "follows" relation is an example of an asymmetric relation. Famous social networking websites such as X and Instagram are some of the use cases of the "follows" relationship, and Facebook presents the "friend" relationship. With the implicit social networking capabilities of an argumentation platform, it is easier to recognize the impact of the social group on the opinions of the user. Collective opinion can manifest in various forms, ranging from a consensus or majority viewpoint to diverse and conflicting perspectives. It is impacted by a variety of things, such as interpersonal relationships, information sharing, societal standards, and personal experiences. Understanding collective opinion is crucial in numerous fields, such as sociology, political science, market research, and public opinion analysis. It allows researchers, policymakers, and organizations to gain insights into the preferences, convictions, and values of a community or target audience. Multiple social networking platforms, e-commerce websites, travel guide websites, and review websites provide this collective opinion by the total number of likes and dislikes using a rating system defined by some scale. However, there are no systematic methods to

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assess the impact of social networks on the collective opinion of cyber-argumentation platforms. In this research, we introduce three kinds of impact: direct impact, group impact, and social group impact. These assessment measures help 1) quantify what a person's individual friends or followers think about one of his or her opinions in an argument. 2) quantify what a person's group of friends or followers thinks about one of his or her opinions in an argument. 3) detection of pseudo-supporters in an argumentation network from a person's friend or follower circle.

In social networks, "pseudo supporters" are those who present a facade of endorsing a certain cause, movement, or philosophy but lack sincere dedication or involvement. These people could seem to be supportive by engaging with the movement's hashtags, likes, sharing, or retweeting information relating to the cause, participating in online debates, or utilizing other strategies. However, their acts frequently show a lack of substance, complexity, or a sincere comprehension of the problems at hand. It's crucial to remember that pseudo-supporters aren't always nasty or purposefully misleading. Their reasons for doing so might be very different, ranging from trying to fit in with the crowd, virtue signaling, adhering to social standards, having limited knowledge on certain topics, or simply wanting to be a part of the latest thing without caring about the problems at hand.

It might be difficult to identify pseudo-supporters on social networks. Metrics such as the number of likes, shares, or follows by themselves could not be a reliable indicator of actual involvement. But having a social network integrated into the cyber-argumentation platform will make the detection mechanism easier. This is due to the availability of opinions provided by users on a wide range of topics.

This article is organized as follows: Section 2 discusses the literature review. Some background about our Intelligent Cyber Argumentation System (ICAS) and its design is described in Section 3. The proposed method for quantifying the impact of social networks on argumentation and the algorithm for finding pseudo-supporters in argumentation are described in Section 4. Section 5 explains the different experiments we ran, and the detailed analysis of the results produced on the Intelligent Cyber Argumentation System (ICAS). Finally, in Section 6, the conclusion is presented.

II. Literature review

Social media platforms or discussion forums are inapt for large-scale deliberations because of discussion fragmentation, difficulty in comprehending, and the amount of effort required to analyze. To overcome this, researchers are leaning towards argumentation platforms. These systems typically employ argumentation frameworks, like IBIS [1] and Toulmin's structure of argumentation [2], to provide structure to discussions, making them easier to analyze. A graphical representation of dialog was designed by an earlier method, gIBIS (graphical IBIS) [3]. While capable of representing issues, positions, and arguments, gIBIS failed to support the representation of goals (requirements) and outcomes. By showing the numerous arguments in a conversation concisely, Computer Supported Argument Visualization (CSAV) systems [4] enhance argumentation. By offering instructional scaffolding that directs students to develop stronger reasoning during conversations, educational tools aim to educate students on various ways to engage in fruitful online argumentation [5]. Klein's Deliberatorium [6] and ICAS , two more sophisticated tools, have incorporated analytical models that describe multiple phenomena that are happening throughout the conversations, like groupthink [7], and opinion consensus [8].

The dynamic social impact hypothesis put forward by Latane has a significant influence since it depicts how other stakeholders in a group interact with one stakeholder at a time [9]. Latane proposed three different principles for the dynamic social impact theory: (1) the social impact or influence received by a target stakeholder within a group is due to the social forces i.e., other stakeholders within the group (2) influence increases as the strength of the social forces 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 [10]. The suggested theory also holds true for a group of participants in argumentation, where influence is communicated through the arguments and the strength of the arguments. In his extensive study, Latane made the point that the groups that are established naturally alter throughout the conversation process as the stakeholders' attitudes shift in the face of counterarguments [11]. The viewpoints of the stakeholders may vary as arguments are exchanged, and stakeholders with similar ideas tend to gather.

From unraveling the intricacies of individual opinion formation to deciphering the mechanisms of information diffusion in social networks, collective opinion propagation models have garnered significant attention among researchers across disciplines. A theoretical model to predict the collective opinion of the steady state given a set of normal users and a small group of opinion leaders was developed by Hou and Lei [12]. With this prediction, we can intervene at the same time in the discussion to steer it in the right direction if it is heading in the wrong path. An experimental study to answer the question "How does the collective opinion of the crowds influence people's credibility judgment and sharing likelihood of health-related statements in social media?" was carried out by Huaye and Yasuaki Sakamoto [13]. The results revealed that the crowd adopted the collective credibility judgment when evaluating the credibility of a statement. When ranking the likelihood of sharing a statement, the crowd also followed the collective sharing likelihood. Different physics-based models are also applied to study the dynamics of collective opinion. The concept of active Brownian particles is used to model a collective opinion formation process by Schweitzer [14]. It is assumed that individuals in a community create a two-component communication field that influences the change of opinions of other people and/or can induce their migration. Michard [15] applied the Random Field Icing Model (RFIM) to study the shifts in collective opinion from smooth trends to abrupt swings depending on the importance of the herding effects. His model considers personal opinion, public information, and social pressure as properties.

III. Background

The research discussed in this paper is built on our previous work of our Intelligent Cyber Argumentation System (ICAS), an online debate platform [16,17,18,19]. It is based on Toulmin's argumentation model [2]. The root of the argumentation tree is an issue. Issues are basically unsolved questions or problems with several solutions. A solution, as the name suggests, is a possible answer or resolution for a specific issue. Under a solution, arguments, which are the opinions of the different users who participated, are present. The arguments in our system have two attributes. One is a text-based description of the user's rationale. Another is the reaction, the stance of the user towards the solution or argument. This reaction is a value selected from the range -1.0 to +1.0 with intervals of 0.2 corresponding to different semantic descriptions like "completely disagree,", "strongly disagree," and so on. The sign of the reaction suggests the user's stance (agreement or disagreement), and the magnitude indicates the intensity of the author's stance. Fig.1 depicts the argumentation structure in the Intelligent Cyber Argumentation System (ICAS).

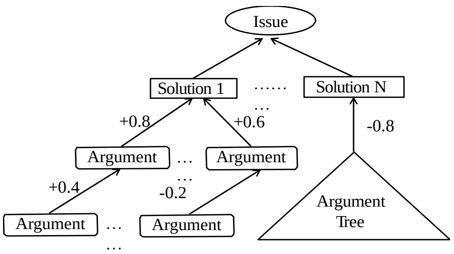

Fig. 1. Sample Argumentation Tree

Multiple key features are implemented in the ICAS. Firstly, it is highly structured and organizes the discourse based on issues instead of time or social connections. This organized structure keeps discussions from becoming fragmented because all pertinent information is gathered in one location. Expressing partial agreements and disagreements towards a solution or an argument under discussion is the first of its kind. Our platform also has social networking features integrated, which encourage user participation. Finally, an artificial intelligence-based backend that contains reasoning and analytical models to analyze the massive discussions. The analytics include collective opinion, polarization index [20], and collective opinion prediction [21].

Considering the argumentation tree, it is always possible to have arguments under arguments at any level. These kinds of arguments do not directly address the solution in the tree. Instead, they are presented in the subtree of an argument. To evaluate the user's opinion, we need to know how these arguments relate to the solution. For this purpose, ICAS uses a fuzzy logic reduction engine. Using fuzzy logic and 25 inference rules, the fuzzy logic engine will reduce an argument's agreement value so that it relates to the parent solution. It will then determine the sign (positive or negative) and the intensity of the agreement level for the reduced argument. The inference rules identify patterns such as implicit support or implicit attacks.

An example of fuzzy logic reduction is shown in Fig. 2. On the left figure, Argument-3 addresses Argument-1 instead of Solution-1. A simple heuristic applied here to determine the sign of the stance of Argument-3 is that attacking (-0.4) the disagreement (-0.8) will make you a supporter of the solution. This way, the Argument-3 in the right of Fig. 2. shows the positive support and the reduced value of 0.5 as magnitude. This same approach can also be extended to every level of the tree. For an in-depth explanation of our fuzzy logic engine, please refer to [18].

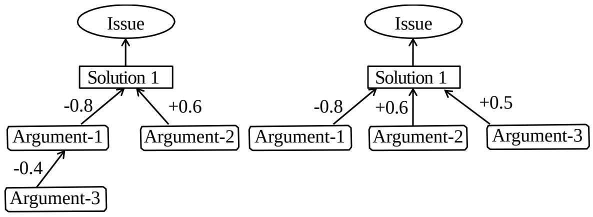

Fig. 2. Fuzzy Logic Reduction. left: Solution tree before fuzzy reduction, right: Solution tree after fuzzy reduction.

IV. APPROACH

Cyber argumentation with social networking has two major components: a cyber argumentation network, and a social network. We developed a social argumentation network as an integrated representation of cyber-argumentation with a social network. In this section, we will present our social argumentation network model first. To quantify the impact of social networks, we defined induced user sets and argumentation support lists. Three types of impacts of social connections on collective opinions in cyber-argumentation are identified, and an algorithm for detecting pseudo-supporters in the social network of an individual person is created. An example is provided to illustrate these models and algorithms.

A. Social Argumentation Network

A social argumentation network is basically a network that presents the interaction of a social network with a cyber-argumentation network. This is based on our previous work; for more details, refer to [22]. In this case, nodes or vertices of the graph are $I{:}\,Set\ of\ Issues,\ S{:}\,Set\ of\ Solutions,$ $A{:}\,Set\ of\ Arguments$ and $U{:}\,Set\ of\ Users$

Let G=<V, E> is graph where

$V = I \cup S \cup A \ \cup \ U$ and

$$E = \{ S \xrightarrow{solves} I, A \xrightarrow{addresses} S, U \xrightarrow{propose} S,$$
$$U \xrightarrow{react} S, U \xrightarrow{react} A, U \xrightarrow{proposes} I,$$
$$U \xrightarrow{argues} A, U \xrightarrow{friends} U, U \xrightarrow{follows} U,$$
$$U \xrightarrow{follows} I, U \xrightarrow{follows} S \}$$

The Social Argumentation Graph (SAG) is defined as $SAG < I, S, A, U, E >$. The small portion of the social argumentation graph built in our Intelligent Cyber Argumentation (ICAS) platform is shown in Fig. 3.

B. Defining Induced User Set

Users who participated in argumentation about a Solution (S) to solve an Issue (I) are called Induced User Set. They can be the owner of a node or the reactor of a node in an argumentation tree. The node in the argumentation graph can be a Solution (S) or Argument (A) in a discussion under an issue.

- *Owner* is basically a user (U) who proposes a Solution ($U \xrightarrow{propose} S$) or who argues an Argument(A) which addresses the Solution ($U \xrightarrow{argues} A$).
- *Reactor* is a user (U) who reacts to Solution or Argument ($U \xrightarrow{react} S, U \xrightarrow{react} A$) with a value between -1 and 1.

$$Induced\ User\ Set\ (U_{node}) =$$
$$\{u_i |\ u_i \xrightarrow{propose} S\ or\ u_i \xrightarrow{react} S\ or\ u_i \xrightarrow{react} A\ or\ u_i \xrightarrow{argues} A\}$$

C. Building the Argumentation Support List (ASL)

This is an adjacency list that contains the list of Support

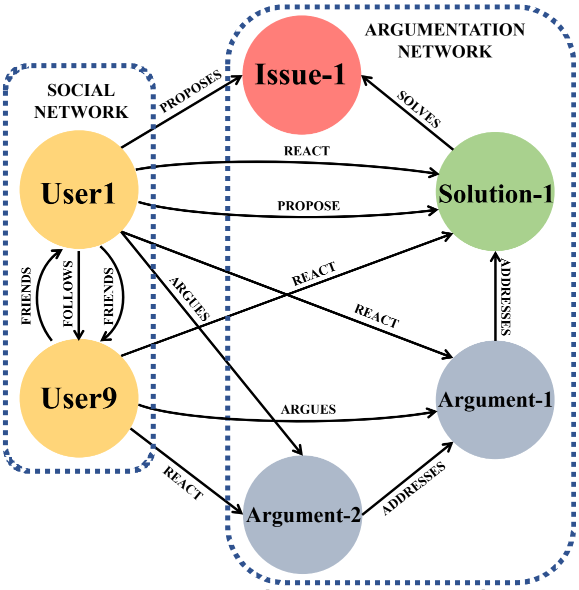

Fig. 3. Simple Argumentation Network

Vectors (SV) for each user with respect to all the other users in the induced user set for all the nodes in the argumentation graph. Each element in the support vector represents the support value provided by the user for another user at a particular node. The support value lies between -1.0 (completely disagree) and +1.0 (completely agree). We use the notation $SV < user_i, node_j, user_k >$ for the support vector of $user_k$ for the $node_j$ owned by $user_i$. Below algorithm shows how to calculate Support Vector $SV < user_i, node_j, user_k >$ for all users in induced user set.

Calculating Support Vector between $user_i, user_k$ $(SV < user_i, node_j, user_k >)$ *for* $node_j$:

Input: $user_i, user_k, SAG < I, S, A, U, E >$

Output: $SV < user_i, node_j, user_k >$)

1. $SV < user_i, node_j, user_k >= \emptyset$
2. $subgraph_{node_j} = \emptyset$
3. Add all arguments (A_{node_j}), induced user set (U_{node_j}), and relationships $(reacts, addresses, argues)$ under the $node_j$ to $subgraph_{node_j}$.
4. For every node in the subgraph, calculate the following and add to Support Vector (SV) of the $user_k$
   a. *Direct Support*: Add the reaction weight of $user_k$ for $node_j$ owned by $user_i$ to SV.
   b. *Indirect Support:* Find all the nodes under the $node_j$. Calculate the reduced weight using the trapezoid fuzzy rule [16,17,18] of those nodes with respect to $user_k$. Add the calculated supports to vector SV.

D. Quantifying the Impact

With the Argumentation Support List (ASL) in place, we define three different types of social network Impacts on a Solution or an Argument for an Issue.

1) Directional Impact

It is defined as the impact of one user on the other user for a solution or an argument. This is calculated as average of all the reaction values provided by the user to a particular node under a solution owned by another user. It can be formally represented as

$$Impact < user_i \rightarrow user_k, node_j >$$

depicting $user_i$ impact on $user_k$ where $node_j$ is owned by $user_k$.

$$Impact < user_i \rightarrow user_k, node_j > = \frac{1}{n} \sum_{i,k} SV < user_i, node_j, user_k >$$

Where $i \neq k$, n is length of $SV < user_i, node_j, user_k >$.

Directional impact has following properties.

i) $Impact < user_i \rightarrow user_k, node_j > \neq Impact < user_k \rightarrow user_i, node_j >$

This is because the reaction weights provided depends on $user_i$ and $user_k$ for the $node_j$

ii) $-1 \leq Impact < user_i \rightarrow user_k, node_j > \leq 1$

where -1 meaning complete disagreement and +1 being complete agreement.

2) Mutual Impact

It refers to impact of two users from the induced user set on a node which can be either solution or argument. It is computed as the mean of Directional Impacts of two users. It is represented as follows.

$$Mutual\ Impact < user_i, user_k > = \frac{1}{|N_i|+|N_k|} \left(\sum_{node_k\ in\ N_k} Impact < user_i \rightarrow user_k, node_k > + \sum_{node_i\ in\ N_i} Impact < user_k \rightarrow user_i, node_i >\right)$$

Where N_i and N_k are nodes owned by $user_i$ and $user_k$ respectively. Like Directional Impact,

$$-1 \leq Mutual\ Impact < user_i, user_k > \leq 1$$

3) Social Group Impact

This determines the impact of a particular group of users in the induced user set on a solution. The group here is related to the social network aspect. This can be group of friends or followers of a user. It is formulated as below.

$$Social\ Group\ Impact(user_i, node_j) = \frac{1}{n} \sum_{user_k in\ F} SV(user_i, node_j, user_k)$$

F is $friends$ or $followers$ of $user_i$ and

$F \in Induced\ User\ Set\ of\ node_j\ (U_{node_j})$

E. Impact Closeness

Impact Closeness tells how far the directional impact or social group impact discussed in an earlier section is from the collective opinion of a node is. Collective opinion is the summation of all the reactions of the users in the induced user set to a solution or argument. The collective opinion is formulated as follows:

$$Collective\ Opinion\ (node_j) = \frac{1}{n} \sum_{user_k inG} SV(user_i, node_j, user_k)$$

Where n is length of each Support Vector (SV)

$$G = Induced\ User\ Set(U_{node_j})$$

$$Directional\ Impact\ Closeness < user_i, node_j, user_k > = CollectiveOpinion(node_j) - Directional\ Impact < user_i, node_j, user_k >$$

$$Social\ Group\ Impact\ Closeness\ (user_i, node_j) = Collective\ Opinion(node_j) - Social\ Group\ Impact(user_i, node_j)$$

As $Social\ Group\ Opinion(user_i, node_j)$, $DirectionalImpact < user_i, node_j, user_k >$ and

$Collective\ Opinion\ (node_j)$ ranges between -1 and +1, we can make some following conclusions

- $-2 \leq Impact\ Closeness \leq 2$
- If $Impact\ Closeness \to 0$, then Social Group Impact or Directional Impact on $node_j$ are supporting towards the $Collective\ Opinion\ (node_j)$.
- If $Impact\ Closeness \to -2$ or $Impact\ Closeness \to 2$, then Social Group Impact or Directional Impact on $node_j$ are attacking the $Collective\ Opinion\ (node_j)$.
- If $Impact\ Closeness\ > 0$ and $Social\ Group\ Opinion\ < 0$ then Group is collectively disagreeing more than overall Collective Opinion.
- If $Impact\ Closeness\ < 0$ and $Social\ Group\ Opinion\ < 0$ then Group is collectively disagreeing less than overall Collective Opinion.
- If $Impact\ Closeness\ > 0$ and $Social\ Group\ Opinion\ > 0$ then Group is collectively agreeing less than overall Collective Opinion.
- If $Impact\ Closeness\ < 0$ and $Social\ Group\ Opinion\ > 0$ then Group is collectively agreeing more than overall Collective Opinion.

To correctly assess the social group impact, we should also consider the friend or follower participation rate of a user. It provides how many of the friends or followers of a user are involved in a discussion under a node. It is defined as follows:

$$Social\ Participation\ Rate(user_i, node_j) = \frac{\left| F(user_i) \cap U_{node_j} \right|}{|\ F(user_i)|} * 100$$

Where F is $friends$ or $followers$ and U_{node_j} is induced user set of $node_j$.

A trade-off should be maintained between impact closeness and social participation rate while finding social groups with great impact. The social groups with a high social participation rate and impact closeness close to zero have a high impact on overall collective opinion.

F. Example

For instance, consider the social argumentation graph shown in Fig. 4., and Table-1 shows the reaction values given by users (u_1, u_2, u_3). To calculate support vector of u_1 and u_2 for node s_1, consider the nodes created by u_1.

Direct Support: For s_1 as it is created by u_1, consider its reaction weight with respect to u_2. It is -0.8. Add this value to the Support Vector.

$$Support\ Vector < u_1, s_1, u_2 > = < -0.8 >$$

Indirect Support: Consider the simplest version of above graph with just having the *addresses*, *react*, *argues* relations as shown in the Fig. 5. Also, let's say $trapezoid\_fuzzy$ is a user defined helper function that takes two reaction weights as inputs and provides the reduced weight by using our fuzzy logic reduction engine as described in Section-3.

1. a_1 is directly addressing s_1, the support value of u_2 for a_1 is fuzzy inference of addresses weight and reaction weight of a_1.
$$trapezoid\_fuzzy(u_2 \to a_1, a_1 \to s_1) = 0.5$$
2. a_2 is addressing s_1 following the path $a_2 \to a_1 \to s_1$. For calculating its support, fuzzy value of reaction weight and reduced value of a_2 with s_1 is used.
$$trapezoid\_fuzzy(u_2 \to a_2, trapezoid\_fuzzy(a_2 \to a_1 \to s_1)) = 0$$

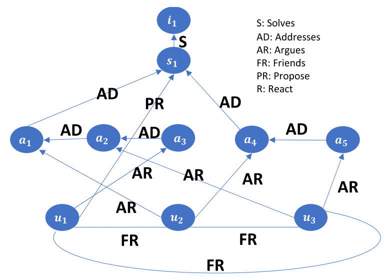

Fig. 4. Example Social Argumentation Graph

User/Node	u_1	u_2	u_3
s_1	0.20	-0.80	0.20
a_1	0.80	0.40	-0.20
a_2	0.20	0.00	0.00
a_3	0.80	0.20	1.00
a_4	-0.80	0.20	0.80
a_5	0.80	1.00	0.00

Table-1 Sample reaction values given by users.

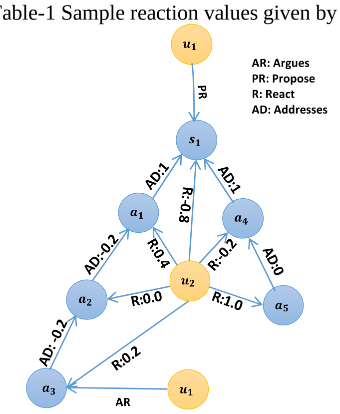

Fig. 5. Simplified Social Argumentation Graph of u_1.

3. Like a_2, calculate the support of a_3
$$trapezoid\_fuzzy(u_2 \to a_3, trapezoid\_fuzzy(a_3 \to a_2 \to a_1 \to s_1)) = 0.008$$
4. On the right branch of the tree, there are a_4 and a_5. Like left branch, by using fuzzy inference support value of a_4 and a_5 with respect to u_2 can be deduced to s_1
$$trapezoid\_fuzzy(u_2 \to a_4, a_4 \to s_1) = -0.2$$
$$trapezoid\_fuzzy(u_2 \to a_5, trapezoid\_fuzzy(a_5 \to a_4 \to s_1)) = 0$$

Finally adding all the indirect supports to support vector,

$$SV < u_1, s_1, u_2 > = < -0.8, 0.5, 0, 0.008, -0.2, 0 >$$

By following the same procedure, the complete Argumentation Support List for the above example is as follows

$$u_1: \{s_1: \begin{Bmatrix} u_2: < -0.8, 0.5, 0, 0.008, -0.2, 0 >, \\ u_3: < 0.2, -0.2, 0.8, 0, 0, 0.04 > \end{Bmatrix},$$
$$a_3: \{u_2: < 0.2 >, u_3: < 1.0 >\}\}$$
$$u_2: \{a_1: \begin{Bmatrix} u_1: < 0.8, -0.04, 0.032 >, \\ u_3: < -0.2, 0, 0.04 > \end{Bmatrix},$$
$$a_4: \{u_1: < -0.8, 0 >, u_3: < 0.8, 0 >\}\}$$
$$u_3: \{a_2: \begin{Bmatrix} u_1: < 0.2, -0.16 >, \\ u_2: < -0.04, 0 > \end{Bmatrix},$$
$$a_5: \{u_1: < 0.8 >, u_2: < 1 >\}\}$$

Using the formulae defined above in quantifying the Impact Section, the Directional, and the Mutual Impacts are calculated as shown in Table-2, Table-3. Finally, calculating the Social Group Impact is as follows. Let u_2 and u_3 are friends of u_1, the $Social\ Group\ Impact\ (u_1,\ s_1) = 0.029$,

Nodes	$u_2 \to u_1$		$u_3 \to u_1$		$u_1 \to u_2$		$u_3 \to u_2$		$u_1 \to u_3$		$u_2 \to u_3$	
	s_1	a_3	s_1	a_3	a_1	a_4	a_1	a_4	a_2	a_5	a_2	a_5
Directional Impact	-0.082	0.2	0.14	1	0.264	-0.4	-0.05	0.4	0.02	0.8	-0.02	1

Table-2 Direct Impact of a user on another user for solutions and arguments

$Collective\ Opinion\ (s_1) = 0.05$ and $Impact\ Closeness = 0.021$. In this case friend support of u_1 is at the distance of 0.021 units from the collective support with the participation rate of 100% i.e., all the friends of user u_1 engaged in the discussion under s_1. Also, as the $Impact\ Closeness > 0$, u_2 and u_3 agreeing less than the overall collective opinion.

Users	Mutual Impact
$< u_1, u_2 >$	0.012
$< u_1, u_3 >$	0.49
$< u_2, u_3 >$	0.33

Table-3 Mutual Impact of User

G. Detection of Pseudo-Supporters of an Individual Social Network

Following is the algorithm we propose to detect the pseudo-supporters. It basically finds users with negative impact from the friend and follower circle of an individual under a solution based on reaction weights provided by them.

$Detection\ of\ \ Pseudo\ Supporters\ (user_i,\ node_j)$

Input: $Suppport\ Vectors < user_i,\ node_j,\ user_k >$ $where\ user_k \xrightarrow{friends/follows} user_i,\ Support\ Tolerance(\delta)$

Output: $Pseudo\ Supporters$

1. $Pseudo\ Supporters\ = \ \emptyset$
2. F=Friends or Followers of $user_i$
3. For every $supporter\ in\ F$
   1. Calculate $Directional\ Impact\ < supporter\ \to\ user_i,\ node_j >$
   2. If $Directional\ Impact < \delta$, Add $supporter$ to $Pseudo\ Supporters$

In the above algorithm, a parameter called Support Tolerance (δ) is used. This controls the magnitude of the impact to be considered while filtering the users based on the impact. Here, as we are considering the existing positive relation "friends" or "follows", the directional impact should be a negative value for being pseudo-supporters. The lower the number, the stronger the attack and vice versa.

V. EXPERIMENTS AND RESULTS

In this section, we present different experiments we ran to assess the impact of social networks on collective opinion in our Intelligent Cyber Argumentation System (ICAS) platform. Argumentation data is collected by using empirical study on our platform and social network data both "*friends*" and "*followers*" data are generated by simulations.

A. Implementation

A responsive web application, Intelligent Cyber Argumentation System (ICAS) [16,17,18,19], was built using standard web technologies such as HTML, CSS, and Javascript, and the back end is coded in the Java programming language. The social argumentation graph was designed using the Neo4j graph database. As discussed in Section-4, this database was created with nodes (issue, solution, argument, and user) and relationships (solves, addresses, propose, proposes, react, argues, friends, and follows). The communication between the client and the server of the application is established using the web socket protocol. The same application was enhanced for implementing these quantifying measures, i.e., directional impact, mutual impact, social group impact, and detecting pseudo-supporters. The screenshot of the same is shown in the Fig. 6.

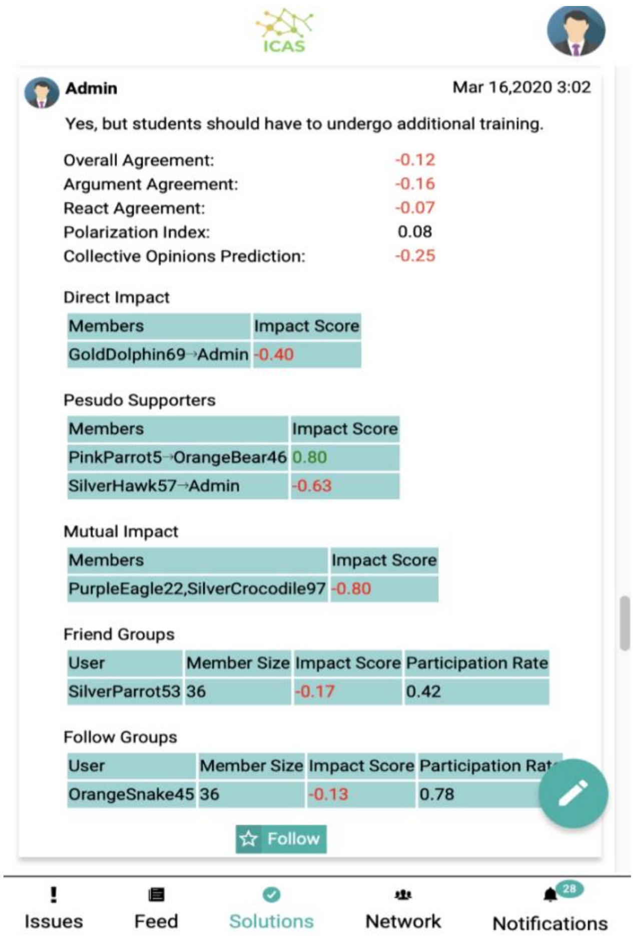

Fig. 6. Direct, Mutual, Social Group Impacts and Pseudo-Supporters in ICAS

B. Empirical Data Description

In a freshman sociology class during the spring 2018 semester, we organized an empirical study. Over the course of five weeks, the class of 344 undergraduate students was asked to discuss various social topics in this empirical study. The study contained four issues, and each issue had four different solutions. For each topic, the students were required to offer at least ten arguments. The final conversation featured almost 10,000 arguments, and 309 students posted an argument or more. Table-4 lists the four issues and solutions that will be discussed in this study.

C. Social Network Configurations

We generated a simulated social network for the argumentation. This simulated social network contains both directed and undirected edges with an edge creation probability of 30% for "*follows*" and "*friends*" relationships respectively.

Issue Name	Solutions
Guns on Campus: "Should students with a concealed carry permit be allowed to carry guns on campus?"	G1: No, college campuses should not allow students to carry firearms under any circumstances.
	G2: No, but those who receive special permission from the university should be allowed to concealed carry.
	G3: Yes, but students should have to undergo additional training.
	G4: Yes, and there should be no additional test. A concealed carry permit is enough to carry on campus.
Religion and Medicine: "Should parents who believe in healing through prayer be allowed to forgo medical treatment for their child?"	R1: Yes, religious freedom should be respected.
	R2: Yes, but only in cases where the child's life is not in immediate danger.
	R3: No but may deny preventative treatments like vaccines.
	R4: No, the child's medical safety should come first.
Same Sex Couples and Adoption: "Should same sex married couples be allowed to adopt children?"	S1: No, same sex couples should not be allowed to legally adopt children.
	S2: No, but adoption should be allowed for blood relatives of the couple, such as nieces/nephews.
	S3: Yes, but same sex couples should have special vetting to ensure that they can provide as much as a heterosexual couple.
	S4: Yes, same sex couples should be treated the same as heterosexual couples and be allowed to adopt via the standard process.
Government and Healthcare: "Should individuals be required by the government to have health insurance?"	H1: No, the government should not require health insurance.
	H2: No, but the government should provide help paying for health insurance.
	H3: Yes, the government should require health insurance and help pay for it, but uninsured individuals will have to pay a fine.
	H4: Yes, the government should require health insurance and guarantee health coverage for everyone.

Table-4 Empirical Data Description for Argumentation Network

D. *Quantifying Impacts*

Directional and Mutual Impact

The direct and mutual impacts of different solutions are depicted in Table-5. We can observe that user "BlueLion87" has a direct impact on user "PurpleBear55" with a value of 0.2, while the overall reaction is 0.21. Similar conclusions can be drawn based on the Table-5. Some of the direct and mutual impacts are missing for solutions as not every solution or argument will be reacted by all the users.

Social Group Impact

a. Friend Network

The group impact scores for the solutions in the issue "Guns on Campus" is shown in the Table-6. For Solution G1, considering the group with friends of the user "BlueCat39", the participation rate of his friends in the discussion is 51%, with an agreement rate of 0.21 and an impact closeness of 0. This is depicted by the purple data points in the Fig. 7. Despite some other users' impact scores being like those of the Collective Opinion, their friend participation ratio is low. This implies that their total influence on collective opinion is weaker. The same can be calculated for all other solutions and issues in Table-6.

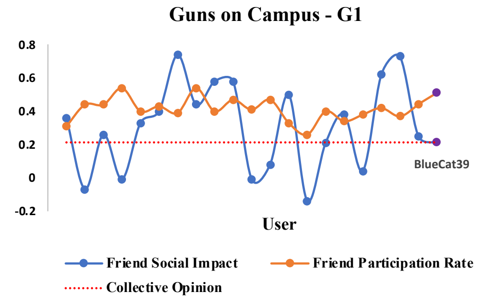

Fig. 7. Impact of Friends on Collective Opinion for Solution G1

b. Follower Network

For calculating the impact of "follows" network, firstly the users in the system are ranked using the Page Rank Algorithm and sorted in the decreasing order of their rank. Now considering the issue 'Same sex couples and adoption", followers of users "PinkEagle49", "PurpleCat10" and "PinkParrot5" have an impact closeness of 0.03 to the overall

Solution	User	Direct Impact	Impact Closeness	Overall Reaction
G1	BlueLion87→ PurpleBear55	0.2	0.01	0.21
	OrangeCat29 → Admin	0.21	0	
G2	OrangeCat75 → Admin	-0.2	0.01	-0.19
G3	GreenBoar68 → PinkDolphin8	-0.4	0.03	-0.37
	GreenBoar68 → SilverEagle10			
R1	PinkGiraffee66 → Admin	0.6	0.02	0.62
R3	SilverParrot53 → Admin	0.2	0	0.20
	BlueDog46→ PurpleBear55	0.2	0	
R3	SilverCrocodile97→ BlueEagle50	0.6	0	0.6
S1	SilveHawk57 → Admin	0.61	-0.19	0.42
Mutual Impact				
S3	BlueLion87, BlueDog46	-0.5	-0.06	-0.56

Table-5 Direct and Mutual Impacts of Solutions for different Issues

collective opinion as shown in the Fig. 8. for solution S1. Impact closeness and the Participation rate of the follower network for all the four issues can be calculated similar to the "friends" section.

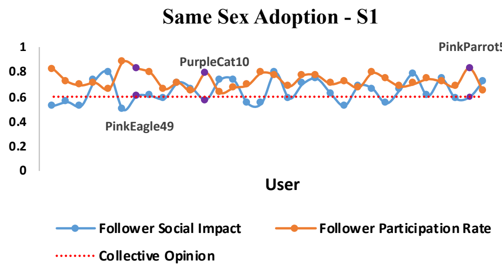

Fig. 8. Impact of Followers on Collective Opinion for Solution S1

E. *Pseudo-Supporters*

We implemented our proposed algorithm for finding the pseudo-supporters specific to a solution in our system. We

Guns on Campus						Same sex couples and adoption					
Solution	User	Group Support	Overall Reaction	Impact Closeness	Participation Rate (%)	Solution	User	Group Support	Overall Reaction	Impact Closeness	Participation Rate (%)
G1	GoldCat75	0.21	0.21	0	40	S1	BlueDog71	0.61	0.60	-0.01	41
	BlueCat39	0.21		0	51		GoldCat75	0.62		-0.02	35
G3	OrangeCat29	-0.05	-0.07	-0.02	29		GoldSnake87	-0.29		0.01	19
	BlueHawk15	-0.09		0.02	37	S3	BlueDog71	-0.43	-0.44	-0.01	17
G4	GoldGiraffe74	-0.38	-0.37	0.01	44		BlueEagle20	-0.46		0.02	12
	BlueLion25	-0.27		-0.1	40	S4	BlueDolphin19	-0.53	-0.56	-0.03	54
Government and Health Insurance						**Religion and Medicine**					
H1	PurpleParrot99	0.10	0.13	0.03	14	R1	SilverParrot53	0.13	0.13	0.0	11
H2	OrangeSnake7	-0.24	-0.23	0.01	16	R2	SilverParrot53	0.19	0.20	0.01	19
	BlueDog71	-0.24		0.01	17		OrangeEagle30	0.17		0.03	17
H3	PurpleParrot99	0.17	0.14	-0.03	20	R3	BlueLion24	-0.24	-0.24	0	13
	BlueDog71	0.10		0.04	24	R4	BlueLion25	0.58	0.62	0.04	23
H4	PurpleParrot99	-0.09	-0.09	0	22		SilverHawk57	0.6		0.02	14

Table-6. Social Group Impacts of Solutions of four Issues

considered the tolerance (δ) as -0.8. Table-7 shows the pseudo-supporters of users in the issue "Guns on Campus".

Guns on Campus		
Solution	**User**	**Pseudo-Supporter**
G1	PurpleCat76	PurpleEagle22, BlueDog71
	SilverDog92	BlueDog71, BlueCat39
	SilverHawk57	PinkCrocodile52, GlodHawk94
G2	GreenShark92	SilverEagle10, OrangeBear69

Table-7. Pseudo-supporters of users in G1, G2

VI. CONCLUSION

In this paper, we developed a methodology to quantify the impact of social networks on argumentation. Three different impacts were introduced: directional impact, mutual impact, and social group impact. These impacts help understand what a person's individual or social group, whether friends or followers, think about his or her opinion. With a simulated social network and argumentation data collected on our ICAS platform, these impacts of the social network on formation of opinions in argumentation were analyzed quantitatively. The experimental results show that our model and algorithm enable detection of pseudo-supporters of individuals on their social networks.

REFERENCES

[1] Werner Kunz and Horst W J Rittel. 1970. Issues as elements of information systems. volume 131, Berkeley.

[2] Toulmin, Stephen Edelston "THE USES OF ARGUMENT," Cambridge, England Cambridge University Press, 1958.

[3] J. Conklin, and M. Begeman, "gIBIS: A Hypertext Tool for Exploratory PoliDiscussion," Transactions on Office Information Systems, 1988.

[4] S. Shum, "The Roots of Computer Supported Argument Visualization," in Visualizing Argumentation: Software Tools for Collaborative and Educational Sense-Making, London: Springer-Verlag, 2003, pp. 3–24

[5] C.-Y. Tsai, C.-N. Lin, W.-L. Shih, and P.-L. Wu, "The effect of online argumentation upon students' pseudoscientific beliefs," Computers & Education, vol. 80, pp. 187–197, Jan. 2015

[6] M. Klein, "How to Harvest Collective Wisdom on Complex Problems: An Introduction to the MIT Deliberatorium," 2011.

[7] M. Klein, "The CATALYST Deliberation Analytics Server," Social Science Research Network, Rochester, NY, SSRN Scholarly Paper ID 2962524, Nov. 2015.

[8] S. Sigman and X. F. Liu, "A computational argumentation methodology for capturing and analyzing design rationale arising from multiple perspectives," Information and Software Technology, vol. 45, no. 3, pp. 113–122, Mar. 2003

[9] B. Latane, "The psychology of social impact," in American Psychologist, vol. 36, pp. 343-356, 1981.

[10] B. Latane, S. Wolf, "The social impact of majorities and minorities," in Psychological Review, vol. 88, pp. 438–53, 1981.

[11] B. Latane, "Dynamic social impact: The creation of culture by communication," in The Journal of Communication, vol. 46, pp. 13–25, 1996.

[12] Hou, Lei, et al. "Prediction of collective opinion in consensus formation." International Journal of Modern Physics C 25.04 (2014): 1450002.

[13] Li, Huaye, and Yasuaki Sakamoto. "The influence of collective opinion on true-false judgment and information-sharing decision." Howe School Research Paper 2013-8 (2013).

[14] Schweitzer, Frank, and J. A. Hołyst. "Modelling collective opinion formation by means of active Brownian particles." The European Physical Journal B-Condensed Matter and Complex Systems 15 (2000): 723-732.

[15] Michard, Quentin, and J-P. Bouchaud. "Theory of collective opinion shifts: from smooth trends to abrupt swings." The European Physical Journal B-Condensed Matter and Complex Systems 47 (2005): 151-159.

[16] Liu, Xiaoqing, et al. "An intelligent computational argumentation system for supporting collaborative software development decision making." *Artificial intelligence applications for improved software engineering development: New prospects*. IGI Global, 2010. 167-180.

[17] Scott Sigman and Xiaoqing Frank Liu. 2003. A computational argumentation methodology for capturing and analyzing design rationale arising from multiple perspectives. Information & Software Technology 45, (2003), 113–122. DOI:https://doi.org/10.1016/S0950-5849(02)00187-8

[18] Xiaoqing (Frank) Liu, Eric Christopher Barnes, and Juha Erik Savolainen. 2012. Conflict Detection and Resolution for Product Line Design in a Collaborative Decision Making Environment. In Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work (CSCW' 12), ACM, New York, NY, USA, 1327–1336. DOI:https://doi.org/10.1145/2145204.2145402

[19] M. M. Rahman, X. "Frank" Liu, J. W. Sirrianni, and D. Adams, "Cross-issue correlation based opinion prediction in cyber argumentation," Argument & Computation, vol. Preprint, no. Preprint, pp. 1–39, Jan. 2021, doi: 10.3233/AAC-200544.

[20] Sirrianni, Joseph, Xiaoqing Frank, and Douglas Adams. "Quantitative modeling of polarization in online intelligent argumentation and deliberation for capturing collective intelligence." 2018 IEEE International Conference on Cognitive Computing (ICCC). IEEE, 2018.

[21] Sirrianni, Joseph W., Xiaoqing Liu, and Douglas Adams. "Predicting stance polarity and intensity in cyber argumentation with deep bidirectional transformers." IEEE Transactions on Computational Social Systems 8.3 (2021): 655-667.

[22] Thota, Bhargav Krishna, Xiaoqing Frank Liu, and Md Mahfuzer Rahman. "Toward Mobile Application of Cyber Argumentation with Social Networking." 2021 IEEE International Conference on Services Computing (SCC). IEEE, 2021.