Aggregation operators to compute norm support in virtual communities[*]

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Abstract

Moderation in virtual communities should not be a private privilege. This paper proposes a method for participants in a social network to decide their own rules for accepting (or not) contents. With the norm argument map, participants are able to argue about norms and voice their opinions about other people's arguments. This structure, equipped with a method to fuse all the data introduced by participants, makes it possible to evaluate the people's support for a norm and decide whether the norm should be applied or discarded.

1 Introduction

With the advent of the Internet, a plethora of on-line communities, such as social networks, have emerged to articulate human interaction. Such fora are not only expected to help humans communicate, but also to facilitate knowledge exchange and the eventual emergence of collective intelligence. Nonetheless, interactions within on-line communities are not frictionless. For instance, users may post inappropriate or offensive contents, or spam ads. Thus, typically the owners of on-line communities establish their own norms (terms and policies) to regulate interactions and punish those that do not abide by them. Moderators enrolled by on-line communities are in charge of guaranteeing the enforcement of such norms.

The deployment of norms comes as no surprise, since they have been widely employed as the rules of the game in our society to constrain human interaction. However, the norms of a virtual community are privately established by its owner (e.g. Facebook) without the involvement of its participants. Thus, these norms disregard what users may deem as fair or discomforting.

Here we take the stance that the participants in a social network must decide the norms that govern their interactions. Thus, we are in line with Nobel-prize winner E. Ostrom [Ostrom, 1990], who observed that involving a community's participants in their decisions improves its long-term operation. Then, there is the matter of helping users agree on their norms. As argued in [Gabbriellini and Torroni, 2015;

Klein, 2012], argumentative debates are a powerful tool for reaching agreements in open environments such as on-line communities. On-line debates are usually organised as threads of arguments and counter-arguments that users issue to convince others so that debates eventually converge to agreements. Users are allowed to express their preferences on arguments by rating them (e.g. [Klein, 2012]). There are two main issues in the management of large-scale on-line debates. First, as highlighted by [Gabbriellini and Torroni, 2015] and [Klein, 2012], there is simply too much noise when many individuals participate in a discussion, and hence there is the need for *structuring* it to keep the focus. Second, the preferences on arguments issued by users must be aggregated to achieve a collective decision about the topic under discussion [Awad *et al.*, 2014].

Against this background, here we consider that structured argumentative debates can also be employed to help users of a virtual community jointly agree on the norms that rule their interactions. With this aim, we present the following contributions:

- Based on the work in [Klein, 2012], we introduce an argumentative structure, the so-called *norm argument map*, to structure a debate focusing on the acceptance or rejection of a target norm.

- A novel aggregation method to assess the *collective support for a single argument* by aggregating the preferences (expressed as ratings) issued by the participants in a discussion. Such method will consider that the impact of a single rating on the overall aggregated value will depend on the distance of that rating from neutrality. More precisely, our aggregation method abides by the following design principle: the farther a rating is from neutrality, the stronger its importance when computing the collective support for an argument.

- A novel aggregation method to compute the *collective support for a norm* based on the arguments issued by the participants in a discussion. This method is based on the following design principles: (1) the larger the support for an argument, the larger its importance on the computation of the collective support for a norm; and (2) only those arguments that are *relevant enough* (count on *sufficient support*) are worth aggregating. Technically, this method is conceived as a WOWA operator [Torra and

Narukawa, 2007] because it allows to consider both the values and the information sources when performing the aggregation of argument supports.

- We compared our aggregation method with a more naive approach that simply averages participants' preferences on a collection of prototypical argumentation scenarios. We observe that our method obtains support values for norms that better capture the collective preference of the participants.

The paper is organised as follows. Section 2 introduces some background on the aggregation operators that we employ in this paper, sections 3, 4, 5, and 6 introduce our formal notion of norm argument map and our operators to compute the support for an argument, a set of arguments and a norm. Sections 7 and 8 detail the analysis of our operator on argumentation scenarios. Finally, section 9 draws conclusions and sets paths to future research.

2 Background

The main goal of this work is to compute an aggregated numerical score for a norm; hence aggregation operators become necessary to fuse all the numerical information introduced by users. The basic concepts used are defined in [Torra and Narukawa, 2007] as follows:

Definition 1. *A **weighting vector** w is a vector such that if $w = (w_1, \ldots, w_n) \in \mathbb{R}^n$ then $w_i \in [0, 1]$ and $\sum_{i=1}^{n} w_i = 1$.*

Definition 2. *Let $w = (w_1, \ldots, w_n) \in \mathbb{R}^n$ be a weighting vector and let $e = (e_1, \ldots, e_n) \in \mathbb{R}^n$ be the vector of elements we want to aggregate. A **weighted mean** is a function $WM_w(e) : \mathbb{R}^n \to \mathbb{R}$, defined as $WM_w(e) = \sum_{i=1}^{n} w_i e_i$.*

Definition 3. *Let $w = (w_1, \ldots, w_n) \in \mathbb{R}^n$ and $q = (q_1, \ldots, q_n) \in \mathbb{R}^n$ be two weighting vectors and let $e = (e_1, \ldots, e_n) \in \mathbb{R}^n$ be the vector of elements we want to aggregate. A **weighted ordered weighted average, weighted OWA or WOWA** is a function $WOWA_{w,q}(e) : \mathbb{R}^n \to \mathbb{R}$ defined as:*

$$WOWA_{w,q}(e) = \sum_{i=1}^{n} p_i e_{\sigma(i)},$$

where σ is a permutation of the elements in e so that $e_{\sigma(i)}$ is the ith largest element in e and:

$$p_i = f^*(\sum_{j \leq i} w_{\sigma(j)}) - f^*(\sum_{j < i} w_{\sigma(j)}),$$

where f^* is a non decreasing interpolation function of the points:

$$\{(i/n, \sum_{j \leq i} q_j)\}_{i=1,\ldots,n} \cup \{(0,0)\}.$$

This function has to be a straight line when the points can be interpolated that way.

3 Norm Argument Map

The concepts of norm, argument, argument set and norm argument map, are formalized as follows:

Definition 4. *A **norm** is an object of the form $n = (\phi, \theta(\alpha))$, where ϕ is the norm's precondition, θ is a deontic operator[1] and α is an action that can be performed by participants.*

Definition 5. *An **argument** is a pair $a_i = (s, \vec{O}_{a_i})$ of a statement s, the argument itself, and a vector of opinions $\vec{O}_{a_i}$ which contains all the opinion values assigned to the argument and provided by the participants.*

Henceforth we will note by $\vec{O}_{a_i} = (o_1^i, \ldots, o_{n_i}^i)$, the vector of opinions, note that o_j^i is the jth opinion about argument a_i. Since each argument a_i has a different number of opinions (n_i), the last opinion about argument a_i is opinion $o_{n_i}^i$.

For the sake of simplicity, we assume that all arguments related to a norm are different and form an argument set.

Definition 6. *Given a norm n, the **argument set** for n is a non-empty collection of arguments $A_n = \{a_1^n, \ldots, a_k^n\}$ containing both the arguments supporting and attacking the norm.*

We will note $\vec{O}_{A_n}$ as the vector of all the opinions of the arguments in A_n.

The argument set of a norm will be then divided into two subsets: the set of arguments in favor of the norm and the set of arguments against it.

We are now ready to define the structure of a norm argument map as follows:

Definition 7. *A **norm argument map** $M = (n, A_n, \kappa)$ is a triple composed of a norm n, a norm argument set A_n, and a function κ that classifies the arguments of A_n between the ones that are in favor of the norm and the ones that are against it.*

For convenience, we will refer hereafter to the two different argument sets that result from the partition of κ over A instead of the norm argument set itself. Specifically, we will denote the set of arguments in favor of norm n (or positive argument set) as A_n^+, being a_i the arguments in it. The set of arguments against the norm (or negative arguments set) will be noted as A_n^-, being $\bar{a}_i$ the arguments in it.

Example 1. *Figure 1 shows an example of a norm argument map in an online sports community. The norm commands to forbid to upload spam in the forum section. The two argument sets (positive/negative) show some example arguments and their corresponding support, in this case in the form of stars.*

Finally, we can also model a framework where participants can discuss multiple norms simultaneously.

Definition 8. *A **norm argument map framework** $F = (P, N)$ is a pair of a set of participants P and a set of norm argument maps N, so that participants in P can deliberate about different norms by means of the norm argument maps in N.*

4 Argument support

Having defined the norm argument map we aim now at aggregating argument's opinions to assess the support for each argument. In our case opinions will be numerical values defined in an opinion spectrum.

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[1]Deontic operators denote prohibition, permission, or obligation.

Figure 1: Example of a norm argument map. As participants rank arguments, circled numbers sequence the subsequent computation of: 1) each argument support; 2) positive and negative argument set support; and 3) norm support.

Definition 9. *An **opinion spectrum** or, simply, **spectrum** is the set λ of possible numerical values individual participants can assign to each argument meaning his/her opinion about that argument.*

The spectrum will be considered a closed real number interval, so maximum, minimum and middle opinion values exist. Since opinions will have different values, we can give different semantics to them. The opinion spectrum will be divided into three subsets of opinions. If we have the opinion spectrum $\lambda = [lb, ub]$, we consider the subset of negative opinions $[lb, \frac{lb+ub}{2})$, the subset of positive opinions $(\frac{lb+ub}{2}, ub]$ and the subset of neutral opinions $\{\frac{lb+ub}{2}\}$. Note that given an argument a_i^n, an opinion $o_j = lb$ is the most extreme opinion against a certain argument, on the other hand, $o_j = ub$ is the most extreme opinion in favor of an argument. Additionally, we consider the opinion laying in the middle of the spectrum $\frac{lb+ub}{2}$ as a neutral opinion.

Figure 2 shows an example of the opinion spectrum semantics considering $\lambda = [1, 5]$.
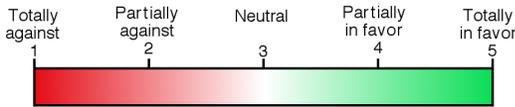
Figure 2: Semantics of the opinion spectrum $\lambda = [1, 5]$.

Since different opinions in an opinion spectrum have different meanings and we aim at aggregating them in order to assess the support for an argument, we need a function that weighs the importance of each opinion, as we consider neutral opinions less important than the extreme (strongly stated) ones.

Definition 10. *Let $\lambda = [lb, ub]$ be a spectrum, an **importance function** is a function $I : \lambda \to [0, 1]$ that for each argument opinion in λ assigns its importance in $[0, 1]$, satisfying the following conditions:*

- *(C1) I has to be a continuous and piecewise differentiable function*
- *(C2) $I(ub) = I(lb) = 1$*

- *(C3) $I(\frac{lb+ub}{2}) = 0$*
- *(C4) If I is differentiable in x, then $I'(x)$ satisfies:*
$$\begin{cases} I'(x) < 0 & if\ x \in [lb, \frac{lb+ub}{2}) \\ I'(x) = 0 & if\ x = \frac{lb+ub}{2} \\ I'(x) > 0 & if\ x \in (\frac{lb+ub}{2}, ub] \end{cases}$$

Given a spectrum, an importance function can be constructed geometrically (parabola case) or by interpolation. We have taken the latter approach, Figure 3 presents the importance function we propose. It suits both the previously defined semantics and imposed conditions. We can now weigh the importance of each opinion with this importance function to assess the support of an argument as the weighted mean of its opinions.

$$\frac{ub^2 - 1.8\ ub\ lb - 0.2\ ub\ x - 4\ lb^2 + 9.8\ lb\ x - 4.8\ x^2}{(lb - ub)^2} \quad \text{when } x \in \left[lb, \frac{ub + 3lb}{4}\right]$$

$$\frac{1.45\ ub + 1.75\ lb - 3.2\ x}{ub - lb} \quad \text{when } x \in \left(\frac{ub + 3lb}{6}, \frac{3ub + 5lb}{8}\right)$$

$$\frac{4\ ub^2 + 8\ ub\ lb - 16\ ub\ x + 4\ lb^2 - 16\ lb\ x + 16\ x^2}{(lb - ub)^2} \quad \text{when } x \in \left[\frac{3ub + 5lb}{8}, \frac{5ub + 3lb}{8}\right]$$

$$\frac{1.75\ ub + 1.45\ lb - 3.2\ x}{lb - ub} \quad \text{when } x \in \left(\frac{5ub + 3lb}{8}, \frac{3ub + lb}{4}\right)$$

$$\frac{-4\ ub^2 - 1.8\ ub\ lb + 9.8\ ub\ x + lb^2 - 0.2\ lb\ x - 4.8\ x^2}{(lb - ub)^2} \quad \text{when } x \in \left[\frac{3ub + lb}{4}, ub\right]$$
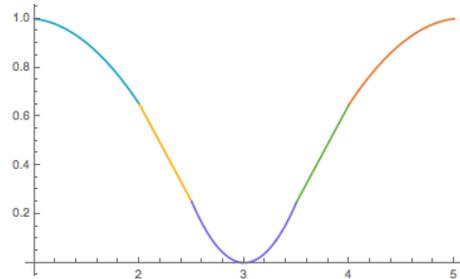
Figure 3: Importance function (I) piece-wise definition and function's plot when $\lambda = [1, 5]$.

Definition 11. *Given an opinion spectrum $\lambda = [lb, ub]$, an **argument support function** $S_{arg} : A \to \lambda$ is a function that*

assesses the collective support for each argument $a_i \in A$ as:

$$S_{arg}(a_i) = WM_w(\vec{O}_{a_i})$$

Where $w = \left(\frac{I(o_1^i)}{T}, \ldots, \frac{I(o_{n_i}^i)}{T} \right)$ stands for a weighting vector for the opinions in $\vec{O}_{a_i}$, I is the importance function and $T = \sum_{j=1}^{n_i} I(o_j^i)$.

Notice that o_j^i is the jth opinion of argument a_i and T the overall addition of all importance values associated to all opinions about argument a_i, so that the elements in w sum one and therefore w is a weighting vector.

5   Argument set support

Since we now know how to aggregate argument opinions into the corresponding argument support, we now face the problem of assessing the support for an argument set. To illustrate the aggregation function chosen, consider the following example:

Example 2. *Consider a norm n with positive and negative arguments with opinions in the spectrum $\lambda = [1, 5]$. Say that there are three positive arguments a_1, a_2, a_3, and a single negative argument $\bar{a}$. On the one hand, in the set of positive arguments a_1 has a support of 5, which comes from a single opinion while both a_2 and a_3 have a support of 1, which comes from aggregating 100 opinions. On the other hand, on the set of negative arguments $\bar{a}$'s support is 5, which comes from aggregating 30 opinions:*

A_n^+	$S_{arg}(a_i)$	$dim(\vec{O}_{a_i})$
a_1	5	1
a_2	1	100
a_3	1	100

A_n^-	$S_{arg}(\bar{a})$	$dim(\vec{O}_{\bar{a}})$
$\bar{a}$	5	30

What should we consider to give the support for A_n^+ on this extreme case? We should discard a_2 or a_3 because they have bad (the minimum possible) support. People have decided that these arguments are not appropriate or do not provide a valid reason to defend the norm under discussion. Since, opinions' semantics can be applied to argument support, arguments with supports outside of $(\frac{lb+ub}{2}, ub]$ are not accepted by participants and, therefore, should not be considered as valid arguments.

We cannot consider a_1 either because although it has the maximum possible support it has only been validated by one person, hence it is negligible in front of the other arguments. We propose here to filter out arguments by just considering those having at least a number of opinions that corresponds to a certain fraction of the number of opinions of the argument with most opinions.

Thus, we tackle this argument relevance problem by creating a new subset of arguments containing only the arguments considered α-relevant and defining the criteria needed to be considered as such:

Definition 12. *Let A be a set of arguments with spectrum $\lambda = [lb, ub]$, a **relevant argument** of A is an argument $a_i \in A$ that satisfies:*

$$S_{arg}(a_i) > \frac{lb + ub}{2}$$

Definition 13. *Let A be a set of arguments with spectrum $\lambda = [lb, ub]$, $alpha \in [0, 1]$ be a relevance level and $a_k \in A$ the argument with most opinions. We say that a_i is an **α-relevant argument** of A if it is a relevant argument of A and also satisfies:*

$$dim(\vec{O}_{a_i}) \geq \alpha \, dim(\vec{O}_{a_k})$$

We note by $R_\alpha(A)$ the set of α-relevant arguments of A.

We propose to aggregate the set of α-relevant arguments by weighting their supports with the importance function previously introduced in order to weight more those arguments that have received more important opinions than others. Moreover, since arguments have different number of opinions, we consider the sum of importances of their opinions so that important opinions account for more weight that neutral opinions.

To aggregate the supports of the arguments weighting these two values we will use a WOWA. Hence we define the argument set support function as such:

Definition 14. *Let λ be an opinion spectrum, an **argument set support function** S_{set} is a function that takes a non-empty argument set A, with $R_\alpha(A) \neq \emptyset$, and gives its support in λ as follows:*

$$S_{set}(A) = WOWA_{w,q}(S_{arg}(a_1), \ldots, S_{arg}(a_{k'}))$$

with $a_i \in R_\alpha(A) = \{a_1, \ldots, a_{k'}\}$ and where:

$$w = \left(\frac{\sum_{j=1}^{dim(\vec{O}_{a_1})} I(o_j^1)}{\tau}, \ldots, \frac{\sum_{j=1}^{dim(\vec{O}_{a_{k'}})} I(o_j^{k'})}{\tau} \right)$$

with $\tau = \sum_{i=1}^{k'} \left(\sum_{j=1}^{dim(\vec{O}_{a_i})} I(o_j^i) \right)$ with $o_j^i \in \vec{O}_{a_i} = \{o_1^i, \ldots o_{n_i}^i\}$

and

$$q = \left(\frac{I(S_{arg}(a_{\sigma(1)}))}{T}, \ldots, \frac{I(S_{arg}(a_{\sigma(k')}))}{T} \right)$$

where $T = \sum_{i=1}^{k'} I(S_{arg}(a_{\sigma(i)}))$, $a_{\sigma(i)} \in R_\alpha(A) = \{a_1, \ldots, a_{k'}\}$ and $a_{\sigma(i)}$ is the α-relevant argument with the ith largest support.

Notice that, if there are no α-relevant arguments then we cannot assess the support for the set, hence we consider $S_{set}(\emptyset)$ to be not defined.

Also note that the w vector is used to weigh the importance of the arguments as the sum of the importances of its opinions, so arguments with more important opinions are considered better information sources. After that we have to divide by τ so we get a weighting vector. The q vector weighs the importance of the values being aggregated (the argument's supports). We have to order the arguments with the σ permutation because the WOWA orders the values being aggregated. This way each weight in the q vector weighs its corresponding element. With this modification, we get WOWA to aggregate the elements using two weighting vectors. Note that the weighting vector w does not have to be ordered because the WOWA itself orders it.

6 Norm support

To assess the support for a norm, we will use the support for its two argument sets $S(A_n^+)$ and $S(A_n^-)$. Note that, a great support for negative arguments has to impact negatively to the norm's support. Thus, instead of aggregating $S(A_n^-)$, we will aggregate $ub+lb-S(A_n^-)$, the symmetric value of the support in the spectrum with respect to the center of the spectrum.

As with the argument set support, we have to weigh the importance of the values aggregated as well as weighting the information sources (the two argument sets). Hence the norm support is assessed as follows:

Definition 15. *A **norm support function** is a function S_{norm} that takes a norm n with non-empty $R_\alpha(A_n^+)$ and $R_\alpha(A_n^-)$ and using its argument set's supports assesses the support for the norm in $\lambda = [lb, ub]$ as follows:*

$$S_{norm}(n) = WOWA_{w,q}(S_{set}(A_n^+), ub + lb - S_{set}(A_n^-))$$

Being w:

$$w = \left(\frac{\sum_{i=1}^{k_1}(\sum_{j=1}^{n_i} I(o_j^i))}{\tau}, \frac{\sum_{i=1}^{k_2}(\sum_{j=1}^{\overline{n_i}} I(\overline{o}_j^i))}{\tau} \right)$$

where $\tau = \sum_{i=1}^{k_1}(\sum_{j=1}^{n_i} I(o_j^i)) + \sum_{i=1}^{k_2}(\sum_{j=1}^{\overline{n_i}} I(\overline{o}_j^i))$, o_j^i *is the jth opinion in $\vec{O}_{a_i} = \{o_1^i, \dots, o_{n_i}^i\}$, $a_i \in R_\alpha(A_n^+) = \{a_1, \dots, a_{k_1}\}$ and $\overline{o}_j^i$ is the jth opinion in $\vec{O}_{\overline{a}_i} = \{\overline{o}_1^i, \dots, \overline{o}_{\overline{n_i}}^i\}$, $\overline{a}_i \in R_\alpha(A_n^-) = \{\overline{a}_1, \dots, \overline{a}_{k_2}\}$.*

And being q:

$$q = \left(\frac{I(S_{set}(A_n^+))}{T}, \frac{I(ub + lb - S_{set}(A_n^-))}{T} \right)$$

where $T = I(S_{set}(A_n^+)) + I(ub + lb - S_{set}(A_n^-))$

If $R_\alpha(A_n^+) = \emptyset$ and $R_\alpha(A_n^-) = \emptyset$, then the norm support is not defined. If only $R_\alpha(A_n^+) = \emptyset$, then the norm support is $S_{norm}(n) = ub+lb-S_{set}(A_n^-)$. Analogously, if $R_\alpha(A_n^-) = \emptyset$, the norm support is $S_{norm}(n) = S_{set}(A_n^+)$.

At this point, having the support for a norm we can decide weather this norm will be enacted or not. Given a pre-defined norm acceptance level μ, a norm will be enacted if $S_{norm}(n) > \mu$. For the norm to be enacted, its support should be laying on the positive side of the spectrum, hence μ should be picked so $\mu \in (\frac{lb+ub}{2}, ub]$.

7 Case study: A virtual community

Using [Torra, 2004], we have coded a package containing the structure and the support functions of the norm argument map and can be found and downloaded in the following site:

https://bitbucket.org/msamsa/norm-argument-map.git

Using this code, we can define the problem of reaching consensus over norms in virtual communities, and comparing the method described in this work with more naive approach. We consider the spectrum to be $\lambda = [1, 5]$, this spectrum can be related to 1-5 star ratings, a commonly used rating method. The importance function used will be the one pictured in Figure 3. We have selected $\alpha = 0.3$ for the α-Relevant arguments.

We will compare this approach to a naive average method, this gives the support for a norm (noted as $S_{avg}(n)$) as the average of all its arguments' opinions (negative argument's opinions are averaged as the symmetric value in the spectrum respect the middle, so that high negative arguments' opinions represent low support for the norm).

Comparison 1. *Consider the next arguments and opinions for norm n:*

- *posarg1 with opinions: 3.5, 3.25, 3.5, 3, 2.5*
- *negarg1 with opinions: 1, 1, 1.2, 1.3, 1.25*

This case represents a weak positive argument, in the sense that people are neutral about it, and a bad negative argument. In this case $S_{avg}(n) = 4$, whereas $S_{norm}(n) = 3.1731$, note that if we required a minimum support of 4 for applying the norm and we used the average naive approach, we would apply the norm, although it does not have a single positive argument with a single positive opinion greater than 4. This happens because the average approach does not use α-relevant arguments. In the case of the project's method the support is more similar to the one expressed in the arguments: a neutral support. Analogously, if considering this same example but with the opinions interchanged, $S_{avg}(n) = 2$ and $S_{norm}(n) = 2.8269$, so the project's method is still neutral whereas now the average approach gives a low support.

A big difference in support happens when arguments are bad and are not enough, such as in this next cases:

Comparison 2. *Consider the next arguments and opinions for norm n:*

- *posarg1 with opinions: 2, 2.5, 1, 3, 2.8*
- *posarg2 with opinions: 1, 1, 1.2, 1.3, 1.25*
- *no negative arguments*

In this case $S_{avg}(n) = 1.705$, but the fact that there are no good arguments does not imply that the norm is not good, because for example in this case, if the norm was not a good norm maybe someone would have given a good negative argument, so maybe the debating period should last more, that way people could give more potentially strong arguments, that is why the support $S_{norm}(n)$ not defined is more adequate.

Analogously:

Comparison 3. *Consider the next arguments and opinions for norm n:*

- *no positive arguments*
- *negarg1 with opinions: 1, 1, 1.2, 1.3, 1.25*

In this case $S_{avg}(n) = 4.85$, but the fact that there is a bad negative argument does not mean that the norm is validated, in fact, as in the previous comparison, this means that maybe the debate should go on, hence in this case $S_{norm}(n)$ not defined is also an adequate support.

A combination of the two previous comparisons (with both bad positive and negative arguments) would be the same

case, $S_{avg}(n)$ would give a not adequate support whereas, $S_{norm}(n)$ would be not defined, which means that maybe the debate should go on.

Another case where the two methods give fairly different supports:

Comparison 4. *Let n be a norm with the following arguments and opinions:*

- *posarg1 with opinions: 5*
- *posarg2 with opinions: 5, 5*
- *negarg1 with opin.: 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1*
- *negarg2 with opin.: 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1*

In this case $S_{avg}(n) = 5$, but note that as previously stated a bad negative argument should not support favorably the norm. Also, the positive arguments have not received big amounts of opinions. If the positive arguments were good enough they would have received more opinions, hence in this case the norm should have a not defined support, which is the case of $S_{norm}(n)$.

Comparison 5. *Let the arguments of norm n be:*

- *posarg1 with opinions: 5, 5, 5*
- *negarg1 with opinions: 3.15, 3.2, 2.8*
- *negarg2 with opinions: 3, 3.5, 2.6*
- *negarg3 with opinions: 2.5, 3.5, 3.2*

In this case $S_{avg}(n) = 3.5375$, whereas $S_{norm}(n) = 4.9842$. Note that, in this case there is a strong positive argument and a few weak or neutral negative arguments, so since people have not found an argument sufficiently strong to attack the norm but they have found a strong argument to enact it, the support should be favorable to the enacting of the norm. In this case if the minimum support to apply a norm was 4, the average method would revoke the norm whereas the proposed method would accept it. This happens because it is fundamental to weigh the importance of the arguments as well as the importance of the argument sets, this way neutral arguments do not weigh much in the overall norm support.

8 Test

A test has been done to evaluate the functionality of the norm argument map. Our test encompassed eleven people debating on certain norms prohibiting posting spam in some sections of a football social network. Each participant was assigned one of the following two roles: regular user (whose behavior was to create positive arguments and give high opinions to other positive arguments); or spammer user (whose behavior was to create negative arguments and give high opinions to negative arguments and low opinions to positive arguments). The test was conducted on two rounds. The first round consisted of a lightly majority of spammer users (4 regular users and 7 spammer users). During the second round, the roles where interchanged, so it consisted of a lightly majority of regular users. The values introduced by participants were aggregated correctly so the implementation of the aggregation method worked successfully and the users debated normally, although we detected some deficiencies in the interface usability.

After the test, participants had to answer a satisfaction survey that included a question asking to evaluate in a scale from 1 to 5 (being 1 the lowest mark, and 5 highest mark) if resulting aggregated ratings were reasonable. The answers given by participants were:

$$5, 4, 4, 3, 4, 2, 3, 3, 3, 2, 4$$

The mean of those values is 3.36. Another important observation is that the participant that performed best his assigned role, namely the one who gave coherent ratings to arguments and placed them correctly, is the one that rated our system with a 5 mark.

Since both values are larger than 3, and understanding that some participants found the interface not comprehensive and might not have understood the system completely, we can conclude that mostly they found the aggregation system fair. Human computer interaction aspects must be carefully considered for future experiments since users were exposed to what they found as a complex argumentation environment; larger experiments are planned as future work.

9 Conclusions and future work

To provide a more democratic way of moderating virtual communities, we propose a new argumentative structure, the so-called norm argument map. We also faced the problem of computing the collective support for a norm from the opinions of an argument's participants. We have identified two core concepts when computing a norm's support: the relevance of arguments and their importance. Thus, we argue that we must only consider relevant enough arguments and weigh opinions based on their importance (strength).

As to future work, we are currently working on identifying similar arguments that should be colapsed, but some other issues, such as when to close the argumentation process or how to define the norm acceptance level μ, still need to be studied. Moreover, we also plan to apply it to other social participation situations such as direct democracy.

References

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