An argumentative approach for discovering relevant opinions in Twitter with probabilistic valued relationships

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Abstract

Twitter is one of the most widely used social networks when it comes to sharing and criticizing relevant news and events. In order to understand the major opinions accepted and rejected in different domains by Twitter users, in a recent work we developed an analysis system based on valued abstract argumentation to model and reason about the social acceptance of tweets, considering different information sources from the social network. Given a Twitter discussion, the system outputs the set of accepted tweets from the discussion, considering two kinds of relationship between tweets: criticism and support. In this paper, we introduce and investigate a natural extension of the system, in which relationships between tweets are associated with a probability value, indicating the uncertainty that the relationships hold. An important element in our system is the notion of an uncertainty threshold, which characterizes how much uncertainty on probability values we are willing to tolerate: given an uncertainty threshold α, we reject criticism and support relationships with probability below α. We also extend our analysis system by incorporating support propagation when computing the social relevance of tweets. To this end, we extend the abstract argumentation framework with a new valuation function that propagates the support between tweets by taking into account not only the social relevance of tweets but also the probability that the support relationship holds, provided that it is above the specified uncertainty threshold α. In order to test these new extensions, we analyze different Twitter discussions from the political domain. Our analysis shows that the social support of the accepted tweets is typically much stronger than the one for the rejected tweets. Also, the set of accepted tweets seems to be very stable with respect to changes to the social support of the tweets, and therefore even when considering support propagation we mainly observe differences in such set when using the more permissive probability thresholds.

1 Motivation and antecedents

Since its inception, in early 2006, Twitter has become one of the fastest-growing and most influential social networks. What started as a simple service to post quick and short, up to 140-character-long, status updates, has grown into one of the keystones of social debate, even being used to promote and organize action, or to empower people politically ([30, 39]).

For instance, when it comes to politics and social issues, Twitter has either been involved in or has helped to create debate, ranging from legislation debate, as in the case of the #TTIP treaty debate, to #guncontrol debates, Wikileaks and Snowden leaks; debates on social unrest, as in #ocuppywallstreet and #spanishrevolution ([22]); or even revolutions and protests, such as the Egyptian and Tunisian revolts in the Arab Spring, also called the "Twitter Revolutions" ([27, 41]), Iranian election protests in 2009, or the Tiananmen commemoration protests in Hong Kong ([31]). From all these cases, it can be seen that the usage of Twitter is not only a status publishing tool (its original intended use), but rather it also serves as an announcement and information dissemination tool, and as a forum-like discussion media, the most interesting use to our study.

In order to understand the major opinions accepted and rejected in different domains by Twitter users, in a recent work we developed a system for analysis of discussions in Twitter ([2]). The system architecture has two main components: a discussion retrieval and a reasoning system. The discussion retrieval component allows us to move from a discussion in Twitter (a set of tweets) in natural language to a specialized structure modeled as a weighted graph, which is computed taking into account two semantic relationships between tweets: criticism and support, and three different attributes of a tweet: the number of followers of the author, the number of retweets and the number of favorites. The reasoning system component maps the weighted graph into a valued argumentation framework and the set of socially accepted tweets in the discussion is evaluated and computed from the weights or values assigned to the tweets in the discussion and the criticism relationships between them.

In this paper we introduce and investigate a natural extension of the system in which relationships between tweets are associated with a probability value, indicating the uncertainty that the relationships hold, and support relationships are propagated between tweets, reinforcing the set of socially accepted tweets in a discussion. In fact, when constructing relationships between tweets from informal descriptions expressed in natural language with other attributes such as emoticons, jargon, onomatopoeia and abbreviations, it is often evident that there is uncertainty about whether some of the criticism and support relationships hold. An important element of our system is the notion of an uncertainty threshold, which characterizes how much uncertainty on probability values we are prepared to tolerate: given an uncertainty threshold α, we would be prepared to disregard criticism and support relationships up to α. We therefore obtain a valued abstract argumentation framework where arguments are tweets, argument values are the weights used to model the relative social relevance of tweets from data obtained from Twitter, and attacks between arguments denote criticism relationships between tweets whose probability of fulfillment is greater than or equal to α. In order to reinforce the set of socially accepted tweets in a discussion, in this work we also propose to extend the system by propagating support relationships between tweets. To this end, we extend the valued abstract argumentation framework with a new valuation function that propagates the support between tweets by taking into account not only the weight of tweets, but also the probability that the support relationship holds, provided that it is above a specified cut-off level α.

We test our system by analyzing the effect of the uncertainty on relationships, the probability thresholds, and the support propagation on different Twitter discussions. Our analysis shows that the social support of accepted tweets is typically considerably stronger than for rejected tweets. Also, the set of accepted tweets seems to be very stable regarding changes to the social support of the tweets, so, even when considering support propagation, we mainly observe differences in such set when using the more permissive probability thresholds.

Given a Twitter discussion the output of the system is the biggest set of tweets of the discussion which can be globally accepted according to the skeptical approach based on the ideal semantics of a valued abstract argumentation framework.

The ideal semantics for valued argumentation guarantees that the set of tweets in the solution is the maximal set of tweets that satisfies that it is consistent, in the sense that there are no defeaters among them, and that all of the tweets outside the solution are defeated by a tweet within the solution. That is, if a tweet outside the solution defeats a tweet within the solution, it is, in turn, defeated by another tweet within the solution. In other words, the solution is the biggest consistent set of tweets that defeats any defeaters outside the solution.

The defeat relationship between tweets is evaluated by combining the criticism and support relationships, according to a given uncertainty threshold, and taking into account the weight of tweets considering different information sources from the social network, such as the number of followers of the author, the number of retweets and the number of favorites. The system can be of special relevance for assessing Twitter discussions in fields where identifying groups of tweets globally compatible or consistent, but at the same time that are widely accepted, is of particular interest, such as for instance for the assistance and guidance of marketing and policy makers.

The rest of the paper is organized as follows. In the next subsection we summarize the more relevant related work within the framework of argumentation models for social context. In Section 2, we define the formal structure to model Twitter discussions, assigning probability values to the relationships between tweets expressing the degree of belief in them, and weights to the tweets expressing their social relevance. Then, in Section 3, we extend the reasoning system with the information provided by support relationships between tweets. Finally, in Section 4 we analyze some Twitter discussions and, in Section 5, we conclude.

1.1 Related work

The idea of considering the relevance of the arguments in argumentation systems applied to social networks has also been studied by [32]. In their work, the authors propose a semantical extension of Dung's Abstract Argumentation Framework ([14]) called Social Abstract Argumentation Framework. This framework incorporates social voting by adding votes for and against arguments, where votes are assumed to be extracted from an online debating system and represent the arguments' strength. Later on, [18] extended the framework to incorporate voting on attacks, including a social notion of attack strengths. The semantics of Social Abstract Argumentation assigns one or more models to debates and is parameterized by a set of operators that characterize how votes should be interpreted, the effect of attacks, and how multiple attacks should be combined. In [13], the authors propose an iterative algorithm to approximate the models of debates structured according to Social Abstract Argumentation.

The exploitation of Twitter by means of argumentation frameworks has also been explored by [24, 25], who defined a framework which allows opinion mining from incrementally generated Twitter queries, triggering the construction of argument trees such as those found in classical Dialogue-based Argumentation ([6]). In their approach, an argument is a set of tweets for a given query (mainly a set of hashtags), and a tree is a hierarchical relation between them, with subsumption and conflict relations. The trees obtained resemble dialectical trees used in their previous work on Defeasible Logic Programming ([38]), although no argumentation algorithm is defined to extract the most relevant arguments from trees.

Our system is close to the argumentation framework developed by [8], where natural language debates are analyzed and the relations among the arguments are automatically extracted. The authors use Bipolar Argumentation algorithms and semantics to evaluate the set of accepted arguments, given the support and the attack relations among them. The arguments and the relations among them are detected by an automated framework by applying natural language techniques, since the system is focused on online debate such as Debatepedia. One key difference between our system and the one proposed by Cabrio and Villata is that we incorporate both weighted arguments and probabilistic valued relationships. Weights are computed from different attributes of a tweet, such as the number of followers of the author, the number of retweets and the number of favorites, while the probability values are computed from informal descriptions expressed in natural language, by means of an automatic labeling system based on Support Vector Machines. We believe that the incorporation of weights and degrees of belief to obtain the relative relevance of arguments and the belief in the attacks, respectively, considering information taken from the social network, is an important aspect if we eventually want to build tools that are useful for analyzing discussions, considering different sources of information for socially accepted arguments. Despite the fact that our argumentation system can be utilized to analyze discussions in different social networks, in this work we focused on the analysis of Twitter discussions that are characterized by a limited number of characters per tweet, the use of emoticons and jargon, and the ability to handle social relevance attributes.

Following Dung's proposal, an argument graph is a graph where each node denotes an argument, and each edge denotes an attack by one argument on another. In the literature we find several extensions to Dung's work that differentiate the strength of arguments and relations between them. In [5], the author defines Value-based Abstract Argumentation by attaching to each argument the social values that it promotes, and making the semantics dependent on a particular preference order over values, representing a particular audience. The Value-based Abstract Argumentation semantics has been used as underlying semantics for defining the notion of argument acceptability in our system. Moreover, our acceptability semantics draws from the so-called "ideal semantics" promoted by [15] as an alternative basis for skeptical reasoning within abstract argumentation settings. In our system, the set of socially accepted tweets of a Twitter discussion is computed by adapting the algorithm for computing the ideal extension for an argumentation framework presented in [16], to work with weights.

In [17], the authors introduce Weighted Argument Systems by extending Dung's framework with weights on the attacks, indicating the relative strength of the attacks or how reluctant we would be to disregard them. These weights are taken into consideration when standard semantics have no models, and one is prepared to accept some contradiction, measured by the weight of the attacks we ignore. This proposal does not consider argument weights and weights on attacks do not express degrees of belief, and it does not therefore directly apply to our case. However this approach introduces the notion of an *inconsistency budget* which characterizes how much inconsistency we are prepared to tolerate. When constructing relationships between tweets from informal descriptions expressed in natural language, it is often evident that there is uncertainty about whether some of the criticisms and support relationships hold. Therefore, in our system we also consider a key element that acts as an uncertainty threshold which characterizes how much uncertainty on degrees of belief we are prepared to tolerate. Thus, our semantic model is based on Value-based Abstract Argumentation where arguments are tweets, argument values are the weights used to model the relative social relevance of tweets from data obtained from Twitter, and attacks between arguments express criticism relationships between tweets whose probability of fulfillment is greater than or equal to an uncertainty threshold.

There have been many developments centered on the extension of argumentation frameworks for reasoning with probabilistic information. [33] extend Dung's framework to form a probabilistic argument framework by associating probabilities with arguments and defeats. These probabilities represent the likelihood of existence of a specific argument or defeat. Later, [28] investigates the foundations of probabilistic argument graphs, [40] defines a probabilistic semantics for pure abstract argumentation frameworks and [21] address the fundamental problem of computing the probability that a set of arguments is an extension according to a given semantics. In [29], the author assigns probability values to attacks between arguments and uses them to obtain a probability distribution over the set of spanning subgraphs of an argument graph as a sample space. The probability distribution over the set of spanning subgraphs is used to determine the probability that a set of arguments is admissible or an extension. In our system, the probabilities of edges of an argument graph are used for pruning purposes and we apply Value-based Abstract Argumentation semantics to solve the resulting graph.

2 Weighted Discussion Analysis in Twitter

As we have already pointed out, our goal is to consider the social network Twitter and to reason, from an argumentative approach, about the set of socially accepted tweets of a Twitter discussion by combining both the social relevance of tweets and the degrees of belief in the answers between tweets. To this end, we model Twitter discussions by means of graphs extended with weights for nodes and edges. The relationships between tweets express answers between them; we say that a tweet t_1 *answers* a tweet t_2 whenever t_1 is a reply to t_2 or t_1 mentions (refers to) t_2. Observe that a tweet can answer many tweets. In what follows, Γ will denote a non-empty set of tweets and will be referred to as a Twitter discussion.

Definition 1 *(Discussion Graph) The Discussion Graph* (DisG) *for a Twitter discussion Γ is the directed graph (T, E) such that for every tweet in Γ there is a node in T and if tweet t_1 answers tweet t_2 there is a directed edge (t_1, t_2) in E. Only the nodes and edges obtained by applying this process belong to T and E, respectively.*

Definition 2 *(Weighted Discussion Graph) A weighted discussion graph* (WDisG) *for a Twitter discussion Γ is a tuple $\langle T, E, L, W\rangle$, where*

- (T, E) *is the* DisG *graph for* Γ.
- *L is a labeling function $L : E \to [0, 1] \times [0, 1] \times [0, 1]$ for edges in E.* [1] *The labeling function L maps an edge (t_1, t_2) to a triple of probability values $(p_c, p_s, p_n) \in [0, 1]^3$ with $p_c + p_s + p_n = 1$, which expresses the probability or degree of belief that the answer from tweet t_1 to tweet t_2 can be classified as criticism (p_c), support*

[1] To simplify the presentation, below we will use the standard notation $\mathbb{D}^3$ to denote the Cartesian product $\mathbb{D} \times \mathbb{D} \times \mathbb{D}$ of a set $\mathbb{D}$.

(p_s) and none (p_n), respectively. Criticism means that tweet t_1 does not agree with the claim expressed in tweet t_2, support that tweet t_1 agrees with the claim expressed in tweet t_2 and none that the relation is none of the previous two.

- *W is a weighting function $W : T \to \mathbb{N}^3$ for nodes in T. The weighting function W maps a node of a tweet $t \in \Gamma$ to a triple of values $(fl, r, fv) \in \mathbb{N}^3$ where fl is the number of followers of the author of tweet t, r is the number of retweets of tweet t and fv is the number of favorites of tweet t.*

Given the weighted discussion graphs obtained from a set of tweets, we are interested in quantifying the social relevance of the tweets and highlight the characteristics we want to analyze. In order to do so, we propose combining the weights of tweets by means of a social valuation function which maps the number of followers, the number of retweets and the number of favorites, to a value in some non-empty set of ordered values R that models the set of social valuation levels.

Definition 3 *(Socially Weighted Discussion Graph) A socially weighted discussion graph* (SWDisG) *for a Twitter discussion Γ is a tuple $\langle T, E, L, W, R, V \rangle$, where $\langle T, E, L, W \rangle$ is the* WDisG *graph for Γ, R is a non-empty set of ordered values, and V is a social valuation function $V : \mathbb{N}^3 \to R$ for the weight of nodes. The social valuation function V maps the weight $W(t) = (fl, r, fv) \in \mathbb{N}^3$ of a node $t \in T$ to a value in R by combining the three sources of information (number of followers, number of retweets and number of favorites); i.e. $V(W(t)) \in R$ for each node $t \in T$.*

In our implementation, we instantiated the set of ordered values R to the natural numbers $\mathbb{N}$ and we considered two valuation functions $V : \mathbb{N}^3 \to \mathbb{N}$:

(1) $V(fl, r, fv) = \lfloor \log_{10}(fl + 1) \rfloor$ which only considers the number of followers and allows us to quantify the tweets' social relevance from the orders of magnitude of authors' followers. We will refer to this function as `followers` valuation function.

(2) $V(fl, r, fv) = \lfloor \log_2(fl + 20 * r + 40 * fv + 1) \rfloor$ which considers not only the number of followers but also the number of retweets and favorites. This function allows us to quantify the orders of magnitude of the social relevance of tweets following the statistics about tweets and retweets defined in [7], trying to give each attribute a weight proportional to its relevance. From the statistics shown in [7], we observe that on weighting with twenty times the value of retweets and forty times the value of favorites, the magnitudes of the three attributes are comparable and one attribute does not dominate the others, since the number of followers is usually much bigger than the number of retweets and favorites. We finally compute the $\log_2$ function of the combined value, since we want to consider that one tweet is more relevant than another only if such combined weight is at least two times bigger for the first tweet. We will refer to this function as `fl1r20fv40` valuation function.

2.1 Argumentation-based analysis

Once we have introduced the formal representation of discussions in Twitter, the next key component is the definition of the argumentation model used to obtain the set of socially accepted tweets of a Twitter discussion. To this end, we use valued abstract argumentation for modeling the weighted argumentation problem associated with the SWDisG graph and ideal semantics defined by [15] for computing its solution (the set of socially accepted tweets). Valued abstract argumentation is based on the extension of abstract argumentation with a valuation function *Val* on a set of values R for arguments and a (possible partial) preference relation *Valpref* between values in R. In our approach, we use Value-based Abstract Argumentation introduced by [4], also called *Audience-specific Value-based Argumentation* in [5], and we consider two thresholds: an uncertainty threshold α which characterizes how much uncertainty on probability values we are prepared to tolerate, and a distance threshold β which characterizes how much uncertainty about classification we are also prepared to tolerate.

Definition 4 *(Valued Argumentation Framework) Let $G = \langle T, E, L, W, R, V \rangle$ be a* SWDisG *graph for a Twitter discussion Γ, let $\alpha \in [0, 1]$ be a threshold on the probability values and let $\beta \in [0, 1]$ be a threshold on the* *distances of the probability values. The Valued Argumentation Framework (VAF) for G relative to the thresholds α and β is a tuple $\langle T, \mathit{attacks}, R, \mathit{Val}, \mathit{Valpref}\rangle$, where*

- *each node (or tweet) in T results in an argument,*
- *attacks between arguments are defined according to the thresholds α and β as follows:*

$$\mathit{attacks} = \{(t_1, t_2) \in E \mid L(t_1, t_2) = (p_c, p_s, p_n) \text{ with } p_c \geq \max(\alpha, p_s + \beta)\},$$

- *R is the non-empty set of ordered values that models the social relevance values of tweets,*
- *the valuation function $\mathit{Val} : T \to R$ for arguments is defined as the social relevance of tweets; i.e. $\mathit{Val}(t) = V(W(t))$, for all $t \in T$, and*
- *$\mathit{Valpref} \subseteq R \times R$ is the ordering relation over R.*

According to this formalization, we obtain a VAF where arguments are tweets, argument values are the weights used to model the relative social relevance of tweets from data obtained from Twitter, and attacks between arguments (or tweets) denote criticism answers between tweets. Moreover, given an uncertainty threshold on the probability values, α, and a threshold on the distances between the criticism and support probability values, β, we obtain a VAF by *pruning the edges* (or answers) (t_1, t_2) between tweets such that the labeling $L(t_1, t_2) = (p_c, p_s, p_n)$ verifies one of the following conditions: (i) the criticism probability value is below the cut level α; i.e. $p_c < \alpha$, (ii) the criticism probability value is lower than the support probability value; i.e. $p_c < p_s$, or (iii) the distance between both probability values is below the cut level β; i.e. $p_c - p_s < \beta$.

Note that although there is no restriction on the values that both thresholds α and β can take, there is a relationship between them that guarantees their validity in the sense that β sets a restriction on the distance between p_c and p_s, and does not override α. We distinguish two cases:

Case $\alpha \geq 0.5$: In this case, β should be in $[2\alpha - 1, \alpha]$.

Case $\alpha < 0.5$: In this case, β should be in $[0, \alpha]$.

To simplify the presentation, from now on we shall refer to an uncertainty threshold on the probability values as an *uncertainty threshold* and to a threshold on the distances between the probability values as a *distance threshold*.

After formalizing the VAF argumentation framework associated with the SWDisG graph, the next key component is the *reasoning model* for discovering relevant opinions of Twitter discussions. To this end, we use the reasoning model that we defined and implemented in [2]. We designed the reasoning model by extending the algorithm for computing the ideal extension for an argumentation framework presented in [16], but adapting it to work with valued arguments. Regarding the implementation, we used an approach based on Answer Set Programming (ASP) described in [19], and available in the argumentation system ASPARTIX, that we extended to work with VAFs, as the current implementation in ASPARTIX only works with non-valued arguments. To develop such an extension we modified the manifold ASP program explained in [20], incorporating the *valuation function* for arguments and the *preference relation* between argument valuations.

Following the approach we already proposed in [2], a *defeat* relation (or effective attack relation) between tweets is defined as follows:

$$\mathit{defeats} = \{(t_1, t_2) \in \mathit{attacks} \mid (\mathit{Val}(t_2), \mathit{Val}(t_1)) \notin \mathit{Valpref}\}.$$

Moreover, a set of tweets $S \subseteq T$ is *conflict-free* if for all $t_1, t_2 \in S, (t_1, t_2) \notin$ *defeats*, and a conflict-free set of tweets $S \subseteq T$ is *maximally admissible* if for all $t_1 \notin S$, $S \cup \{t_1\}$ is not conflict-free and, for all $t_2 \in S$, if $(t_1, t_2) \in$ *defeats* then there exists $t_3 \in S$ such that $(t_3, t_1) \in$ *defeats*. Finally, given an uncertainty threshold α and a distance threshold β, the *set of socially accepted tweets* of a Twitter discussion Γ, referred to as the *solution* of Γ, is defined from the VAF $\langle T, \mathit{attacks}, R, \mathit{Val}, \mathit{Valpref}\rangle$ relative to the thresholds α and β, and it is computed as the largest admissible conflict-free set of tweets $S \subseteq T$ in the intersection of all maximally admissible conflict-free sets.

Consider the following example of a discussion, that it is a piece of the first discussion analyzed in Table 1 of Section 4. We show the text (translated from Spanish) of each tweet and its social value or weight, computed using the `fl1r20fv40` valuation function:

Tweet 1 Text: *"Minister Morenes, if you have searched for this "surprise" photo to eclipse the story of @ZaidaCantera, YOU WILL NOT GET IT "* . Weight: 22. This is the root tweet.

Tweet 2 Text: *"@MaderoCandelas @jordievole @ZaidaCantera If the facts have consistency there are many places where it is possible to do it, I tell you from experience"*. Weight: 8. This tweet replies to **Tweet 1**.

Tweet 3 Text: *"@Arnau63 @jordievole @ZaidaCantera True, but I have to clarify that I was a simple Soldier and thanks to my work destination I saw constant abuse"*. Weight: 9. This tweet replies to **Tweet 2** and mentions the author of **Tweet 1.**

Tweet 4 Text: *"@jordievole @ZaidaCantera Of the gasoline mafia... that was awesome "*. Weight: 11. This tweet replies to **Tweet 1.**

After labeling each answer (replies and mentions), with the SVM labeling model that we explain in Section 4, we obtain that tweet 2 supports tweet 1 with probability 0.56, tweet 3 supports tweet 1 with probability 0.51 and attacks tweet 2 with probability 0.82, and tweet 4 attacks tweet 1 with probability 0.52. With this information, in the VAF for the discussion and with $\alpha = 0.5$ and $\beta = 0.1$, tweet 1 is accepted in the solution, given that none of its attackers defeats it (given their weights). Additionally, tweet 2 is defeated by tweet 3, and tweet 3 and 4 are accepted because they are not defeated by any other tweet. So, tweet 2 is rejected and tweets 1, 3 and 4 are the maximal set of accepted tweets. We note that there might be an attack between two tweets in the solution, if this relation of attack is not effective; i.e. if this attack relation does not result in a defeat relation due to the social value or weight of tweets. For instance, in this example, we have tweet 4 attacking tweet 1 although both tweets are in the solution, since tweet 4 does not defeat tweet 1 due to the fact that the weight of tweet 1 (22) is greater than the weight of tweet 4 (11).

2.2 Study case

The system architecture has two main components: the discussion retrieval and the reasoning system. The discussion retrieval component takes a discussion Γ on a tweet, referred to as *root tweet*, and outputs its SWDisG graph according to a social valuation function V on a set of values R. The reasoning system component takes the SWDisG graph and outputs the solution of Γ based on the ordered set of values R and the social valuation function V, and relative to an uncertainty threshold α and a distance threshold β.

Figure 1 shows the solution computed by the reasoning system for a Twitter discussion obtained from the political domain. To compute the solution, we considered the uncertainty threshold 0.6 and the distance threshold 0.2. A thin arrow with a black arrowhead from node A to node B indicates that tweet A criticizes tweet B with a degree of belief greater than or equal to 0.6, while a wide arrow with white arrowhead indicates that tweet A supports tweet B with a degree of belief greater than or equal to 0.6. [2] The discussion has a simple structure, possibly one of the most frequent in Twitter. A root tweet starts a discussion, wherein the majority of tweets support the root tweet, some replies criticize it, and very few replies are between non-root tweets. The discussion contains 23 tweets, 13 attack edges and 18 support edges. Each tweet is represented as a node, where the root tweet of the discussion is labeled with 0 and the other nodes are labeled with consecutive identifiers according to the temporal generation order of the tweets in the social network.

The nodes colored in red are the tweets in the solution and the nodes colored in gray are the rejected tweets, where the darkness of the color is directly proportional to its social value or weight. In this case, we evaluated the social relevance of tweets through the `followers` valuation function. In [1], we also analyzed this discussion using a valuation function based on the number of retweets, but without considering the probabilities on the edges, since it is the first time that we study its management in the extraction of relevant opinions in Twitter. The results show that there is a slight difference between both attributes (followers and retweets) and the main differences are on the tweets with no answer (nodes whose input degree is zero). Thus, in the present work, we only present the results referring to the number of followers.

The solution contains 16 out of the 23 tweets, only 7 tweets being rejected because there are more supporting

[2] Note that A can support (respectively, criticize) B with a degree of belief less than or equal to 0.4, since the uncertainty threshold has been set at 0.6 and the distance threshold at 0.2.

than attacking answers and also because out of the 13 attack edges only 7 produce effective attacks or defeats, which are the ones that cause 7 tweets to be outside the solution: tweets 1, 2, 3, 4, 5, 9 and 16. Note that the solution contains attacks between them ($17 \to 10$, $10 \to 0$ and $7 \to 0$) because these attacks do not produce effective attacks, given the social value of these tweets.

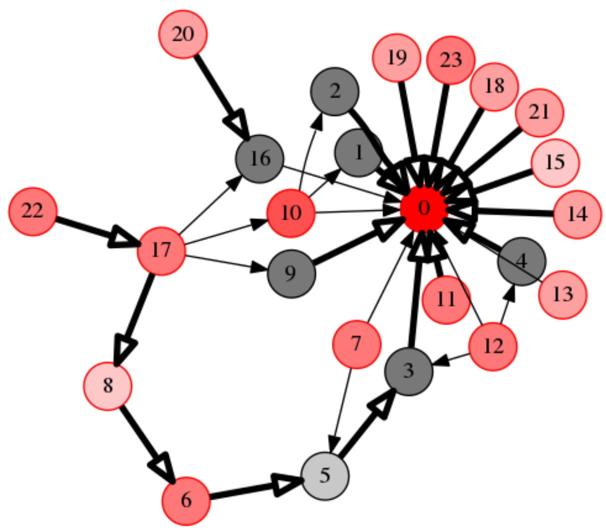

Figure 1: SWDisG solution based on the number of followers.

3 Support propagation

In our system, the interaction between a pair of tweets (t_1, t_2) of a Twitter discussion is characterized as an answer from t_1 to t_2 and is mapped to a triplet of probability values $(p_c, p_s, p_n) \in [0, 1]^3$ expressing the degree of belief that tweet t_1 criticizes the claim expressed in tweet t_2, t_1 supports the claim expressed in tweet t_2 and that the relation between them is neither of these, respectively. It is worth noting that although we handle such probability values, given an uncertainty threshold α and a distance threshold β, the defeat relation (or effective attack relation) between tweets is evaluated from the answers for argument pairs according to the fact that $p_c \geq \max(\alpha, p_s + \beta)$ and a preference relation between argument valuations. Thus, in order to reinforce the set of socially accepted tweets in a discussion, we propose extending the system by propagating support relationships between tweets. To this end, we extend the VAF argumentation framework with a new valuation function that propagates the support between tweets by taking into account not only the social relevance of tweets but also the probability that the support relationship holds, provided that it is above a specified uncertainty threshold α.

In the literature we find different approaches to incorporate support between arguments in the context of Abstract Argumentation Frameworks. [10] introduce Bipolar Abstract Argumentation and propose extending the defeat relation with indirect attacks with the additional constraint that, if B supports C and A attacks B then A also attacks C. In [9] Bipolar Abstract Argumentation was extended with a gradual interaction-based valuation process with the aim of assessing the quality of the defeat relation.

In our framework, we could also consider the characterization with indirect attacks for tweet pairs that are not (direct) answers, by using the information from the supports answers; i.e. if t_1 answers, but does not attack t_2, and t_3 attacks and defeats t_1, and t_3 does not answer t_2, then we could also consider that t_3 attacks t_2, whenever the fact that t_1 answers, but does not attack t_2, is interpreted as the fact that t_1 supports t_2. This approach was proposed in the system defined by [8], and the authors used Bipolar Argumentation Frameworks to extract such indirect relations from online debates where arguments and relationships between them are extracted from much more textual information than typical tweets. In our system, since we consider Twitter discussions where the classification on relationships handles a great deal of uncertainty, we found that the information contained in a typical tweet almost never allows us to consider a sound indirect attack between tweets t_3 and t_2, if t_3 is not an answer for t_2.

However, it seems appropriate to use the support relationships to reinforce the weight of tweets within a Twitter discussion which can lead to different defeat relations between them. The idea is that if B attacks C, but B does not defeat C due to its social relevance, and tweets $A_1, A_2, \ldots, A_n$ support B, then the weight of B can be increased by combining its weight with the weights of A_1, A_2, …, A_n. Thus, the new weights for B and C can lead to a new solution where B defeats C, since B

attacks C. In our system, the weight of a tweet is the triplet $(\mathit{fl}, r, \mathit{fv}) \in \mathbb{N}^3$ obtained on setting each value to its corresponding attribute value (followers, retweets and favorites) from the tweet. It therefore seems appropriate to propagate these weights between tweets that are supported within a Twitter discussion Γ and, thus, the support propagation mechanism should take into account the weight of a tweet t, the weight of each tweet that supports t in Γ, the degree of belief to which each of them supports t in Γ and some aggregation functions to combine all these values.

Definition 5 *(Support extended VAF) Let G $=\langle T, E, L, W, R, V\rangle$ be the* SWDisG *graph for a Twitter discussion Γ, let $\alpha \in [0,1]$ be an uncertainty threshold and let $\beta \in [0,1]$ be a distance threshold. Moreover, let $\sqcup : \mathbb{N}^3 \times \mathbb{N}^3 \rightarrow \mathbb{N}^3$ be an element wise aggregation function non-decreasing (element wise) in the first argument and let $\sqcap : [0,1] \times \mathbb{N}^3 \rightarrow \mathbb{N}^3$ be a balancing function. The Support extended VAF for G with respect to the thresholds α and β and the functions $\sqcup$ and $\sqcap$, is the VAF $\langle T, \mathit{attacks}, R, \mathit{Val}^*, \mathit{Valpref}\rangle$, where the valuation function $\mathit{Val}^* : T \rightarrow R$ for arguments is defined in the following way:*

$$\mathit{Val}^*(t) = \begin{cases} V(W(t)), & \text{if } \mathit{support}(t) = \emptyset \\ V((W(t) \sqcup (p_{s_1} \sqcap W(t_1))) \sqcup \ldots \sqcup (p_{s_n} \sqcap W(t_n))), & \\ \qquad \text{if } \mathit{support}(t) = \{(t_1, p_{s_1}), \ldots, (t_n, p_{s_n})\} & \end{cases}$$

with

$$\begin{aligned} \mathit{support}(t) \;=\; & \{(t_i, p_{s_i}) \in (T \times [0,1]) \mid (t_i, t) \in E \textit{ and} \\ & L(t_i, t) = (p_{c_i}, p_{s_i}, p_{n_i}) \textit{ with } p_{s_i} \geq \max(\alpha, p_{c_i} + \beta)\}. \end{aligned}$$

The support of a tweet $t \in \Gamma$ is the set of tweets that support t together with the degree of belief to which each of them supports t in Γ. When the support of a tweet t contains two or more tweets, the evaluation of the aggregation function $\sqcup$ in $\mathit{Val}^*(t)$ is performed from left to right, ensuring that $\mathit{Val}^*(t) \geq \mathit{Val}(t)$, since $\sqcup$ is element wise non-decreasing in the first argument. However, it may occur that a tweet t in the solution of the VAF for G, based on the social valuation function $\mathit{Val}(t)$, is rejected in the support extended VAF due to the fact that it not only changes the value of t, but also that of all the tweets of the discussion.

Functions $\sqcup$ and $\sqcap$ allow us to parameterize the Support extended VAF. Some interesting definitions for the aggregation function $\sqcup$ are the element wise sum function and the element wise maximum function, referred to hencefor as sum function and maximum function, respectively. The sum function takes into account not only the weight of the tweets that support a tweet, but also the number of tweets that support it, while the maximum function subtracts relevance from the number of tweets that support it. For instance, if the support of a tweet $t \in \Gamma$ is the set of pairs $\{(t_1, p_{s_1}), \ldots, (t_n, p_{s_n})\}$ with $p_{s_1} \sqcap W(t_1) \geq p_{s_i} \sqcap W(t_i)$, for all $i = 2, \ldots, n$, and the $\sqcup$ function is the maximum function, the value $\mathit{Val}^*(t)$ is equivalent to the case when the tweet t is only supported by the tweet t_1. However, if the $\sqcup$ function is the sum function, $\mathit{Val}^*(t)$ leads to different values depending on the tweets in the support set. The function $\sqcap$ allows us to consider the degree of belief of the support relations in the support set. If $\sqcap$ is the identity function for the second argument, its effect is to not consider the probability values of the support relations in the support set, while the product function emphasizes support relations with a high degree of belief.

It is worth noting that the support propagation model is local in the sense that function $\mathit{Val}^*(t)$ is not propagated from a leaf tweet t (tweet with a in-degree zero) to the root tweet, allowing us to give more relevance to direct than to indirect supports. Thus, if tweet t_1 supports tweet t_2 and tweet t_2 supports tweet t_3 (t_1 indirectly supports t_3), $\mathit{Val}^*(t_3)$ leads to an equal or lower value than when both t_1 and t_2 (directly) support t_3.

Next we analyze the solution for the Support extended VAF of the discussion introduced in the previous section. We considered two different support propagation functions Val^*, one based on the maximum and the other on the sum. Figures 2 and 3 show the graph instance solutions for the maximum and sum aggregation functions $\sqcup$, respectively. In both cases, the balancing function $\sqcap$ is the identity function for the second argument, giving the maximum and the sum functions for support propagation. For the case of the maximum function, tweets 10, 1 and 2 change their status. In this case, the weight of tweet 17 is increased by spreading the weight of tweet 22 and, consequently, the weight of tweet 10 is lower than the recalculated weight of tweet 17 and, thus, the attack $17 \rightarrow 10$ is effective, which leads to rejecting tweet 10 and to accepting tweets 1 and 2 since, although the attacks $10 \rightarrow 1$ and $10 \rightarrow 2$ are effective, tweets 1 and 2 are defended

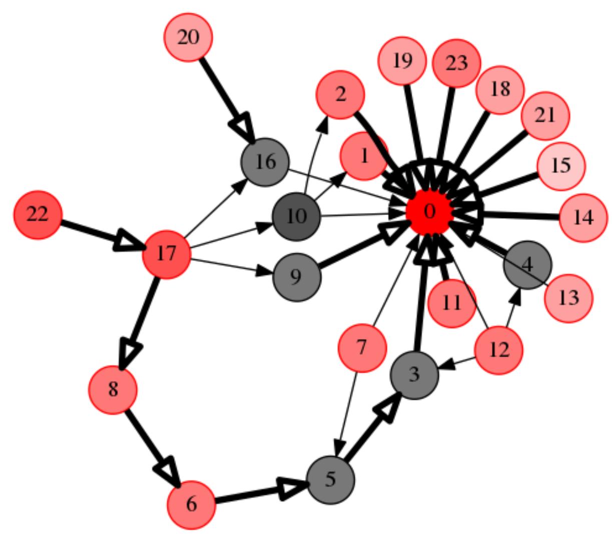

Figure 2: SWDisG solution with maximum support propagation.

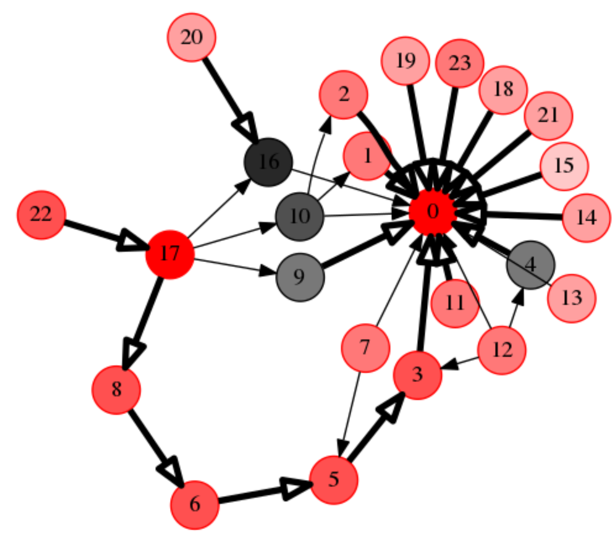

Figure 3: SWDisG solution with sum support propagation.

by tweet 17 in the solution. Obviously, the sum function produces higher increases in the weight of the tweets with more support answers than the maximum function. This is why, with the sum function, tweets 3 and 5 change their status and become part of the solution.

4 Analysis of Twitter Discussions

We now analyze six Twitter discussions, in the political domain, obtained with our discussion retrieval system. [3] To obtain the SWDisG instances corresponding to these discussions, our system first creates the DisG from each discussion, downloading the tweets with the Twitter API and finding the set of answer tweets for each discussion's tweet. Our system allows us to analyze any set of tweets. In this work we deal with discussions where a tweet only answers previous tweets, and therefore the graphs obtained are acyclic. The corresponding WDisG is derived by computing the labeling function for edges with a support vector machine (SVM) model and the triplet (fl, r, fv) of each tweet is obtained by setting each value to its corresponding attribute value (followers, retweets and favorites) from the tweet. The SVM model is built from a set of 582 pairs of tweets (answers) obtained from a discussion set on Spanish politics, and manually labeled with the most probable label (support, criticism or none). To build the SVM model, for each pair of tweets we extract different features: occurrences of words from a Spanish dictionary with 200 non-stop words and 50 stop words, number of images, emoticons, sentiment expressed by the text, and cosine distance between the word vectors of the two tweet texts. We use the sentiment analysis module from [36] and [26], which provides a sentiment value in the range $[-5, +5]$, but we increment (or decrement) such a value considering the number of positive and negative emoticons present in the tweet. We used LibSVM ([11]) to train a probabilistic SVM model, that is, a labeling function that assigns a triplet of probabilities (p_c, p_s, p_n) to each answer (t_1, t_2). LibSVM implements multiclass classification using one-against-all methods. Having n classes, $\binom{n}{2}$ binary classifiers are constructed. Then, each point to be predicted is classified according to each of the $\binom{n}{2}$ binary classifiers, giving one vote to the class (or classes) to which it has been assigned. Finally, the point

[3] The files with all the discussions analyzed in this section can be found at `http://ai.udl.cat/remository/func-startdown/22/`

is assigned to the class with the highest number of votes received. Then, the probability estimates can be obtained using the likelihood methods of [37]. LibSVM uses the same Platt method but algorithmically improved ([34]).

As an RBF (Radial Basis Function) kernel is employed, two parameters must be specified during training. First, the penalty parameter of the error term in the optimization equations (C). Second, the exponent constant of the RBF kernel (γ). Both parameters are set to default values, with $C = 1$ and $\gamma = 1/n_f$, being n_f the number of features. With these values the accuracy of the obtained SVM model over our training set is 75%. The SWDisG is obtained by combining the triplet (fl, r, fv) of each tweet with the `fl1r20fv40` valuation function, To test our system with support propagation, we use one aggregation function $\sqcup$, the sum, and two different balancing functions $\sqcap$, the identity (giving sum support propagation) and the product (giving weighted sum support propagation).

Table 1 shows the analysis of the solutions for the corresponding VAF and Support extended VAFs for the SWDisG of each discussion, where each VAF has been solved with two different pairs of values for the α and β thresholds: $(\alpha, \beta) = (0.5, 0.1)$ and $(\alpha, \beta) = (0.3, 0.01)$. For each discussion we show three rows, the first one for the solution of the VAF (with no support propagation), the second one for the solution of the Support extended VAF with sum support propagation, and the third one for the solution of the Support extended VAF with weighted sum support propagation.

Each discussion is identified with a shortened URL that points to the source discussion in Twitter. For each discussion we show the number of tweets of the discussion ($|T|$), the percentage of accepted attack edges (aa) and the percentage of accepted support edges (as).[4]

Next, for each (α, β) case, we also show the size ratio of the solution ($|S|$) to $|T|$, the number of defeaters[5] inside the solution to number of defeaters outside the solution ratio ($\frac{def_{in}}{def_{out}}$), a measure of how deep the discussion is between accepted and rejected tweets (C_{depth}) and the sum of social values for accepted tweets to the sum of social values for rejected tweets ratio ($\frac{\sum_{in} v}{\sum_{out} v}$). The C_{depth} value is defined as the length of the longest alternating path between accepted and rejected tweets, i.e. a path with attack edges where an accepted tweet is followed by a rejected tweet, and vice-versa. We finally show the symmetric difference between the solution obtained without support propagation and the solution obtained with sum and weighted sum propagation ($| \triangle |$).

Overall, we observe that the sum of social values for tweets in the solution is bigger than for the rest of tweets (in some discussions several times bigger). This observation, together with the fact that the number of defeaters also tends to be larger in the solution, indicates that the social relevance of the accepted tweets is significantly higher than for the rejected ones. Because a defeater tweet inside the solution can be a defeater for several tweets outside the solution, the fact that the $\frac{def_{in}}{def_{out}}$ ratio is always bigger than 1 indicates that the solution is based on many different tweets, that defeat the tweets outside the solution, and such that small changes to the weights of the tweets would probably not make significant changes to the solution, because the more defeaters you have in the solution, the less likely it is that small changes to the relevance of some tweets will make a significant change in the solution. This fact probably explains the small differences between solutions obtained with or without support propagation. We observe that the defeaters ratio and the sum of social values ratio do not change significantly in many discussions, and the symmetric difference obtained is typically small, although bigger differences are observed for the largest discussions, at least with the sum support propagation and especially when using the more permissive values for (α, β).

We believe that support propagation makes only a significant difference in discussions where there are tweets with low values for their (fl, r, fv) triplet, but with many replies supporting those tweets. Somehow, this indicates a situation in which the real relevance was not well measured by the more direct indicators (fl, r, fv) and the supporting replies helped to adjust the relevance towards a more realistic value. But we believe that, high values for (fl, r, fv) of a tweet appear usually connected with a high number of support replies for that tweet. Regarding the controversy depth C_{depth}, the higher values are found for discussions where the solution size is close to half the

[4]The value aa is the percentage of edges such that $p_c \geq \max(\alpha, p_s + \beta)$ with respect to the edges such that $p_c \geq p_s$ and as is the analogous value for support edges, i.e. it is the percentage of edges such that $p_s \geq \max(\alpha, p_c + \beta)$ with respect to the edges such that $p_s \geq p_c$.

[5]A tweet t_1 is a defeater if there is a pair (t_1, t_2) in the *defeats* set.

Table 1: Analysis results for six Twitter discussions with the `f1lr20fv40` valuation function and with no support propagation, with sum support propagation and with weighted sum support propagation.

		$(\alpha, \beta) = (0.5, 0.1)$						$(\alpha, \beta) = (0.3, 0.01)$					
Discussion URL	|T|	(aa, as)	$\frac{\|S\|}{\|T\|}$	$\frac{def_{in}}{def_{out}}$	C_{depth}	$\frac{\sum_{in} v}{\sum_{out} v}$	Δ	(aa, as)	$\frac{\|S\|}{\|T\|}$	$\frac{def_{in}}{def_{out}}$	C_{depth}	$\frac{\sum_{in} v}{\sum_{out} v}$	Δ
goo.gl/m4RON9	32	(86,47)	0.59	3.00	9	1.87		(96,100)	0.59	3.00	9	1.87	
with sum			0.59	3.00	9	1.87	0		0.59	3.00	9	1.87	0
with weighted sum			0.59	3.00	9	1.87	0		0.59	3.00	9	1.87	0
goo.gl/NGEWrr	57	(75,83)	0.95	3.0 / 0	6	18.47		(100,98)	0.95	3.0 / 0	6	18.47	
with sum			0.95	3.0 / 0	6	18.47	0		0.95	3.0 / 0	6	18.52	0
with weighted sum			0.95	3.0 / 0	6	18.47	0		0.95	3.0 / 0	6	18.47	0
goo.gl/E3NCa8	68	(44,68)	0.95	3.0 / 0	4	25.5		(88,97)	0.96	3.0 / 0	4	25.5	
with sum			0.94	3.00	3	25.18	2		0.91	2.50	3	8.71	7
with weighted sum			0.95	3.0 / 0	4	28.78	0		0.96	3.0 / 0	4	29.4	0
goo.gl/ftyIJ7	78	(94,85)	0.72	2.33	17	2.39		(98,99)	0.71	2.33	17	2.39	
with sum			0.73	2.33	17	2.55	1		0.73	1.90	17	2.52	3
with weighted sum			0.72	2.33	17	2.33	0		0.72	1.90	17	2.29	2
goo.gl/RnFJ39	95	(98,52)	0.52	2.83	41	1.60		(99,97)	0.52	2.83	41	1.60	
with sum			0.51	2.77	39	1.55	3		0.51	2.76	41	1.55	3
with weighted sum			0.53	2.91	41	1.62	2		0.51	2.76	41	1.55	3
goo.gl/AZHa9a	142	(78,81)	0.86	1.57	8	6.83		(100,99)	0.81	1.44	8	4.56	
with sum			0.86	1.50	10	6.94	2		0.80	1.66	7	4.67	2
with weighted sum			0.86	1.71	8	7.08	0		0.80	1.66	7	4.57	2

number of tweets, and it therefore shows a pattern in the discussion where the opinions are highly polarized in two groups of almost the same size, and where users are trying to defend their positions strongly with long discussion chains. The more extreme example for this behavior is found in discussion 5 of the table, where the C_{depth} value is around half the size of the discussion.

Finally, to further validate our observations, in Table 2 we analyze four test sets of Twitter discussions. Each test set is identified, in the first column, with the range for the number of tweets in the discussions, denoted as the size in brackets. The second column ($|dis|$), shows the number of discussions of each test set. All the root tweets have been obtained searching in Twitter with the hashtag: #PedroSanchez (an Spanish politician). We show the median values for the same characteristics we have analyzed in Table 1. This time, for each test set there are two rows, the first one for the solution of the VAF (with no support propagation) and the second one for the solution of the Support extended VAF with sum support propagation. Given that sum support propagation seems to give a higher difference than weighted sum support propagation, we have ommitted that row for the sake of clarity. Basically, we observe the same results as before: a value around 2.0 for the defeaters ratio, higher values for the sum of social values ratio, small (or zero) symmetric difference between the solution for no support propagation and the solution for sum support propagation, and high-

Table 2: Analysis of median values for four test sets of Twitter discussions.

		$(\alpha, \beta) = (0.5, 0.1)$						$(\alpha, \beta) = (0.3, 0.01)$					
test set	$\lvert dis \rvert$	(aa, as)	$\frac{\lvert S \rvert}{\lvert T \rvert}$	$\frac{def_{in}}{def_{out}}$	C_{depth}	$\frac{\sum_{in} v}{\sum_{out} v}$	Δ	(aa, as)	$\frac{\lvert S \rvert}{\lvert T \rvert}$	$\frac{def_{in}}{def_{out}}$	C_{depth}	$\frac{\sum_{in} v}{\sum_{out} v}$	Δ
size $[20-25]$	10	(80,100)	0.95	$1.5/0$	2	16.91		(100,100)	0.95	$1.5/0$	2.5	16.91	
with sum			0.95	$1.5/0$	2	17.20	0		0.95	$1.5/0$	2.5	17.20	0
size $[40-47]$	10	(60,91)	0.84	2.87	4	6.80		(94,98)	0.83	1.72	4.5	6.06	
with sum			0.84	2.42	3.5	7.08	0		0.83	1.46	4.5	6.44	0
size $[52-58]$	8	(75,69)	0.73	0.87	6	2.60		(97,97)	0.63	1.12	7	1.64	
with sum			0.73	0.77	6	2.67	2		0.67	1.00	7	2.10	4
size $[72-93]$	8	(83,81)	0.72	2.39	15	3.00		(99,98)	0.68	2.37	15.5	2.64	
with sum			0.72	2.51	15	3.13	0.5		0.68	2.57	15.5	2.76	1

est C_{depth} value for the test set with discussions with the highest balance between accepted and rejected tweets (in this case, the last test set).

5 Discussion and conclusions

In our previous work [2], we designed and implemented a reasoning system based on valued argumentation frameworks for the extraction and analysis of relevant opinions in Twitter discussions. Then, in [1], we started to study the extension of the previous system with a support propagation model. In this paper we introduce and investigate a natural extension of the system in which a relationship between two tweets is associated with a triplet of probability values which expresses the degree of belief of two tweets' relationship, being classified as criticism, support and none. The introduction of this information leads to a reasoning system based on a new valued argumentation framework that uses a new attack relation between tweets that is defined on the basis of an uncertainty threshold and a distance threshold. Moreover, this information also leads to the redefinition of the support propagation model given the uncertainty information added to the support set of a tweet.

The new reasoning system is tested with real Twitter discussions from the political domain. The analysis of these Twitter discussions allows us to extract the largest consistent set of tweets that are widely accepted socially, called solution of the discussion. We observe that the sum of the weights of the tweets in the solution always seems to be greater than the sum of the tweets outside the solution. Moreover, the number of defeaters in the solution seems to be at least twice the number of defeaters outside the solution.

To test our system with support propagation we use the sum and the weighted sum functions. To explore alternative functions to perform the propagation, we plan to study the use of the OWA operator (Ordered Weighted Averaging, [42]). The OWA operator has already been used in argumentation systems like in [35], where the OWA operator is used to aggregate the degrees of individual preferences on a given position.

As a future work, we plan to analyze social networks different to Twitter, for which information in favor and against an argument can be explicitly obtained. Twitter is not the only social network to elicit researchers' interest. Other, more conversational networks, with longer messages, such as Reddit, have also been the focus of recent research, with works, such as [12], analyzing subjacent characteristics of the conversation patterns with several statistical measures like virality or responsiveness of the threads, or which kind of participations users have: heavy writers or early responders. Considering social networks where discussions tend to have more lengthy texts, we could also consider the use of argumentation frameworks that use more structured arguments, like DeLP ([23]) or its more recent extension: the weighted argumentation framework RP-DeLP ([3]), which adds several defeasibility levels to the propositional logic knowledge base and is based on a recursive ideal semantics.

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