Analysis of Discussions in Twitter with an Argumentation Tool

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Analysis of Discussions in Twitter

The analysis of opinions on general and specialized social networks, has recently received a lot of attention on many application fields. For example, there is a vivid interest in the analysis of opinions of tourists about destinations and facilities, aimed at getting insight on tourist behavior and preferences for improvement and investment policy planning (McCarthy and Stock 2010; Villatoro et al. 2013; Williams et al. 2015), and similar efforts are being done on marketing (Burton and Soboleva 2011), customer engagement (Zhang, Jansen, and Chowdhury 2011), and related fields (Jansen et al. 2009; Chu and Kim 2011). Less numerous are the contributions centered around analyzing, not individual opinions, but debates and conversations where the structural relations between opinions are a key component to be able to pinpoint the accepted, or winning, opinions in a discussion. In this line, key contributions are the works of Atkinson et al. about using argumentation for tools to support e-participation in deliberation processes (Atkinson, Bench-Capon, and McBurney 2006; Cartwright and Atkinson 2008; 2009; Wardeh et al. 2013).

Although there exist many specialized and generalist social networks, nowadays Twitter is one of the most widely used ones when it comes to share and criticize relevant news, and the citizens response to news and events in Twitter is frequently taken as an indicator of the social interest for that topic. In order to understand what are the major accepted and rejected opinions in different domains by Twitter users, in a recent work (Alsinet et al. Submitted to Elsevier Science) we have developed a system for analysis of discussions in Twitter. The system architecture has two main components: a discussion retrieval system and a reasoning system. The discussion retrieval system allows us to move from a discussion in Twitter (a set of tweets) in natural language to a specialized structure called Weighted Labeled Discussions Graph (WLDisG) which is computed taking into account two semantic relationships between tweets: criticizes and supports, 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 maps the WLDisG graph into a valued argumentation framework (VAF) and the set of socially accepted tweets in the discussion is computed from the weight assigned to each tweet and the criticism relationship, as the ideal extension of the VAF associated with the WLDisG graph of the Twitter discussion.

Our system is close to the argumentation framework developed by Cabrio and Villata (Cabrio and Villata 2013). The authors use bipolar argumentation algorithms 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 debates, such as Debatepedia, where user posts tend to have a rich structure that allow natural language methods to infer semantic relationships.

One key difference between our system and the one proposed by Cabrio and Villata is that we incorporate weighted arguments, by means of different weighting schemes, and define attacks between them by means of preference relations over the weights. We believe that the incorporation of weights to get the relative relevance of arguments, considering information taken from the social network, is an important aspect if we want to finally build tools that are useful for analyzing discussions considering different sources of information for widely socially accepted arguments. Although our argumentation system can be utilized to analyze discussions in different social networks, in this work we have focused on the analysis of Twitter discussions. The discussions extracted from Twitter are characterized by: limited number of characters by tweet, use of emoticons and jargon, and social relevance attributes present in tweets. From these elements, we compute weighted arguments and relations between them by means of an automatic labeling system based on Support Vector Machines.

An Argumentation Tool

The *Weighted Labeled Discussion Graph* (WLDisG) for a non-empty set of tweets Γ is a tuple $\langle T, E, L, W_R \rangle$, where:

- (T, E) is a directed graph such that for every tweet $t \in \Gamma$ there is a node in T and where if tweet t_1 answers tweet t_2 there is a directed edge (t_1, t_2) in E, [1].
- L is a labeling function

$$L : E \to \{\textit{criticizes}, \textit{supports}, \textit{none}\}$$

[1] 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.

for edges (t_1, t_2) in E, *criticizes* meaning that a tweet t_1 does not agree with the claim expressed in tweet t_2, $supports$ that tweet t_1 agrees with the claim expressed in tweet t_2 and $none$ if the relation is none of the previous two.

- W_R is a weighting function $W_R : T \rightarrow R$ that assigns a weight value in an ordered set R to each tweet in T, representing the social relevance of the tweet.

We have considered three weighting schemes, based on followers, retweets, and favorite count of a tweet, that give place to three different weighted graphs, and we have used the same function for the three kinds of graphs, a function that maps the input value w (followers, retweets or favorites) to a logarithmic scale that in our case is $\lfloor \log_{10} w + 1 \rfloor$.

Figure 1 shows the WLDisG graph instance for a Twitter discussion obtained from the political domain using the followers weighting scheme. 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 there are not many replies between non-root tweets. The discussion contains 23 tweets, 13 attack edges and 18 support edges. Each tweet is represented as a vertex, where the root tweet of the discussion is labeled with 0 and the other vertices are labeled with consecutive identifiers. An arrow with black arrowhead from vertex A to vertex B indicates that tweet A criticizes tweet B, while an arrow with white arrowhead indicates that tweet A supports tweet B. [2] The set of vertices are colored in *blue scale* where the darkness of the color is directly proportional to its weight; i.e. the darkness of the color represents the number of followers of the authors of the tweets with respect to the maximum value in the discussion.

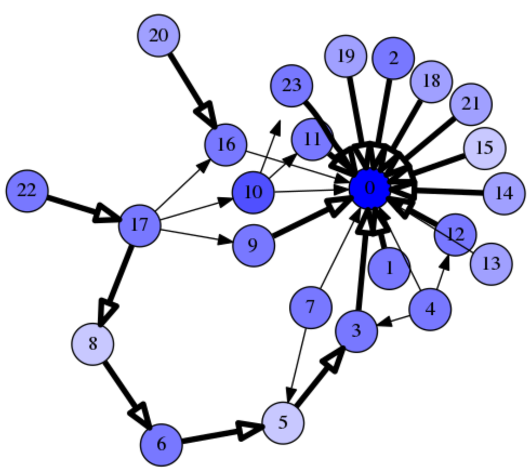

Figure 1: Discussion graph using the followers weighting scheme.

Once we have introduced our formal representation of discussions in Twitter, the next key ingredient is the reasoning system used to obtain the set of socially accepted tweets. To this end we have used a valued abstract argumentation framework (Bench-Capon 2003) for modeling the weighted argumentation problem associated with WLDisG and ideal semantics (Dung, Mancarella, and Toni 2007) for defining its solution (the set of socially accepted tweets). In particular the set of socially accepted tweets of a set of tweets Γ, referred as the *solution* of Γ, is computed as the largest admissible conflict-free set of tweets in the intersection of all maximally admissible conflict-free sets.

Figure 2 shows the solution computed by the reasoning system for the WLDisG graph of Figure 1. The vertices colored in red are the tweets in the solution and the vertices colored in gray are the rejected tweets, where the darkness of the color is directly proportional to its weight. The solution contains 16 of the 23 tweets and only 7 tweets are rejected. This is because there are more supporting answers than attacking ones and also because from the 14 attack edges only 7 produce effective attacks (defeats) given the weights of the tweets, that are the ones that cause seven tweets to be outside of the solution: tweets 3, 5, 9, 11, 12, 16 and 23.

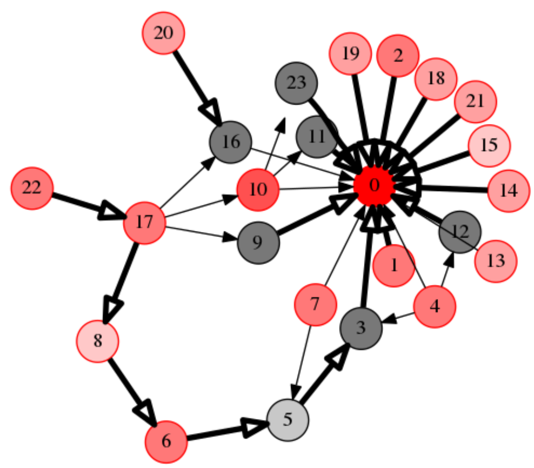

Figure 2: Discussion graph solution.

Tool Design

For discussion retrieval we have a web application based on the `Django` framework which allows:

- Downloading a conversation from Twitter given a root tweet and displaying all the tweets in the conversation.
- Displaying the WLDisG graph related to the conversation, by selecting the weighting scheme (followers, retweets or favorites). The relations can be manually edited.
- Saving all the gathered conversations and conversation graphs in a database, allowing the offline access of data by external tools.

The reasoning system is based on the ASPARTIX system (Egly, Gaggl, and Woltran 2008) for solving the VAF problem instance obtained from a WLDisG graph.

[2] We are working also in an extension of our system where support relations will be used to modify the weights of the tweets.

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