



Empowering an E-Government Platform Through Twitter-Based Arguments ¹

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Abstract Social networks have grown exponentially in use and have gained a remarkable impact on the society as a whole. In particular, microblogging platforms such as Twitter have become important tools to assess public opinion on different issues. Recently, some approaches for assessing Twitter messages have been developed. However, such approaches have an important limitation, as they do not take into account contradictory and potentially inconsistent information which might emerge from relevant messages. We contend that the information made available in Twitter can be useful for modeling arguments which emerge bottom-up from the social interaction associated with such messages, thus enabling an integration between Twitter and defeasible argumentation. In this paper, we outline the main elements characterizing this integration in the context of a particular e-government platform (Decide 2.0). As a result, we will be able to obtain an “opinion tree”, rooted in the first original query, in a similar way as done with dialectical trees in argumentation. The main contribution of this paper is the proposal of a method for building arguments from aggregated opinions. This leads to the design of a novel platform that makes it possible to explore collective opinions in a more meaningful and systematic manner.

Keywords: Argumentation, E-government, Social media.

1 Introduction and motivations

Social networks have grown exponentially in use and impact on the society as a whole, aiming at different communities and providing differentiated services. In particular, microblogging has become a very popular communi-

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cation tool among Internet users, being Twitter² by far the most widespread microblogging platform. Created in 2006, Twitter enables its users to send and read text-based posts of up to 140 characters, known as “tweets”. The diffusion of Twitter in the society is so high that governments around the world are considering how to benefit from it; for example assessing public opinion on different issues based on tweets. Thus, for example, nowadays it is common to read newspaper articles referring to the impact of political decisions measured by their associated positive or negative comments in Twitter. Symmetrically, policy makers use social media tools, like Twitter, to make their claims and opinions public, having a more direct access to the citizenry and prompting them to “tweet back” with further comments and opinions³. As the audience of microblogging platforms and services grows everyday, data from these sources can be used in opinion mining and sentiment analysis tasks [14].

As pointed out in [17], microblogging platforms (in particular Twitter) offer a number of advantages for opinion mining. On the one hand, Twitter is used by different people to express their opinion about different topics, and thus they are a valuable source of people’s opinions. Given the enormous number of text posts, the collected corpus can be arbitrarily large. On the other hand, Twitter’s audience varies from regular users to celebrities, company representatives, politicians, and even country presidents. Therefore, it is possible to collect text posts of users from different social and interests groups.

From a meta-level perspective, policy makers devote much effort in analyzing the reasons underlying complex collections of opinions from the citizenry, as they indicate the willingness of the people to accept or reject some particular issue. A well-known example in this setting is the analysis of public opinion (e.g. through the quantitative measurement of opinion distributions through polls and the investigation of the internal relationships among the individual opinions that make up public opinion on an issue). Additionally, a fundamental need for policy makers is to back their decisions on reasons or opinions provided by citizens. They might even argue with other policy makers about why making a particular decision is advisable (e.g. “according to the last poll, 80% of the people are against the health system reform; therefore, the reform should not be carried out”). From this perspective, social networks like Twitter provide a fabulous knowledge base from which information could be collected and analyzed in order to enhance and partially automatize decision making processes. In particular, tweets (i.e., messages posted on Twitter) have a rich structure (see Figure 1), providing a number of record fields which allow to detect provenance of the tweet (author), number of re-tweets, followers, etc.

We contend that the information made available from such tweets can be useful for modeling opinions which emerge bottom-up from the social interaction existing in Twitter. In our analysis, we will assume that opinions *are* arguments, which can be seen as instances of the “Argument from Majority” schema [3, 20]. Opinions will have associated sentiments⁴, which might be conflicting, so that counter-opinions might appear. This might lead to a tree-like structure for a dialectical analysis, similar to the one applied in argumentative systems, such as DeLP [10]. In this paper, we analyze the main elements characterizing a possible integration of Twitter and defeasible argumentation. We present a particular algorithm for exploring tweets relevant to a particular hashtag, finding whether it is supported by a positive or negative opinion, obtaining as well other alternative counter-opinions. As a result, we will be able to obtain an “opinion tree”, rooted in the first original query.

The rest of the paper is structured as follows. In Section 2, we outline the main elements characterizing Decide 2.0, a platform intended to provide an integration of social media and argumentation as an e-government infrastructure. Section 3 presents an overview of argumentation theory, distinguishing the salient elements in any argumentation system. In Section 4 we analyze the parallels between argumentation and Twitter, discussing alternatives for modeling Twitter elements in argumentative terms. Section 5 discusses a proposal for exploring Twitter messages in terms of “opinion trees”, which capture arguments associated with different hashtags; while two examples to illustrate the proposal are presented in Section 6. Section 7 discusses related work, and Section 8 concludes this work.

2 Decide 2.0: integrating argumentation and social media

Government 2.0 refers to government’s adoption of Web 2.0 technologies to socialize government services, processes, and data [16, 8]. Enabling new ways of communication - text, audio, video as well as two-way communications, Government 2.0 provides new mechanisms for government agencies to:

²<http://www.twitter.com>

³E.g. the current UK Prime Minister David Cameron and the current US President Barack Obama can be followed on Twitter at @Number10gov and @BarackObama, respectively.

⁴Several software tools have been recently developed for such an association, such as <http://www.sentiment140.com>.

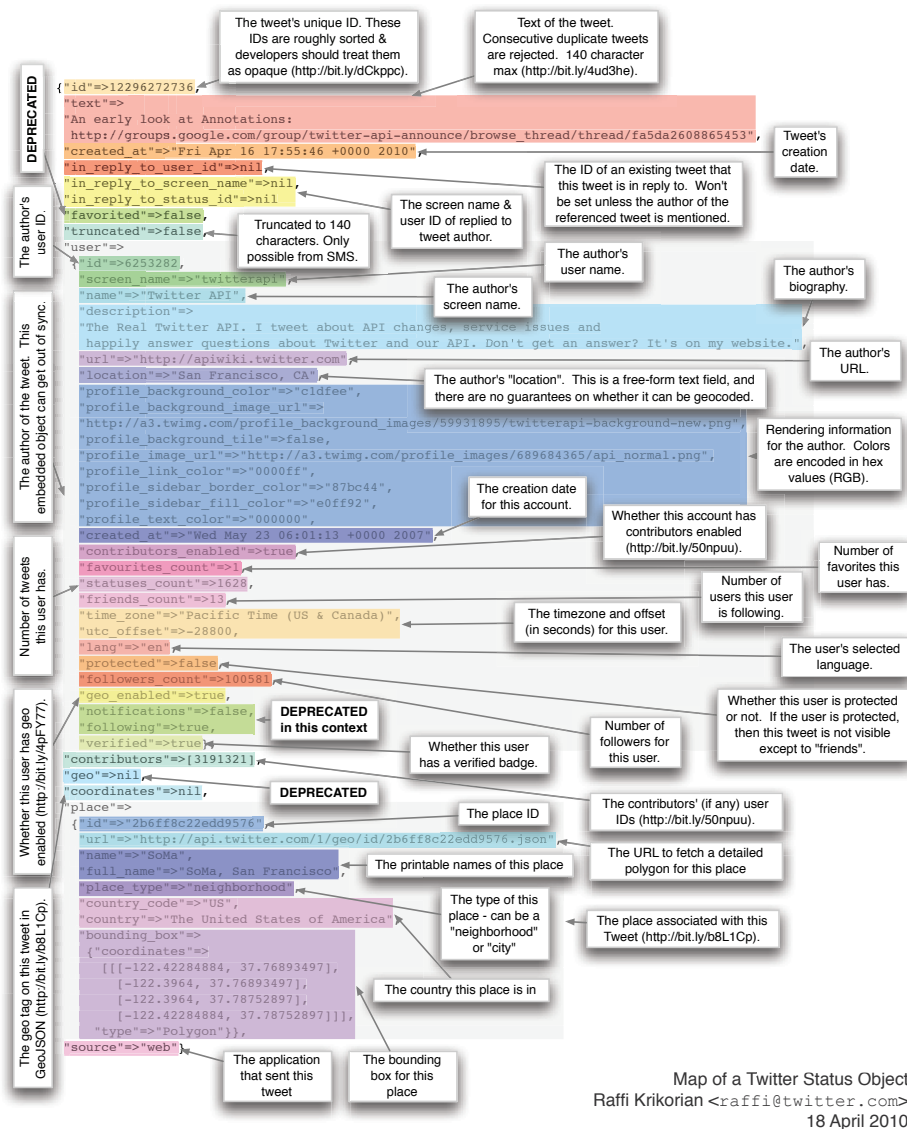


Figure 1: Map of a Tweet

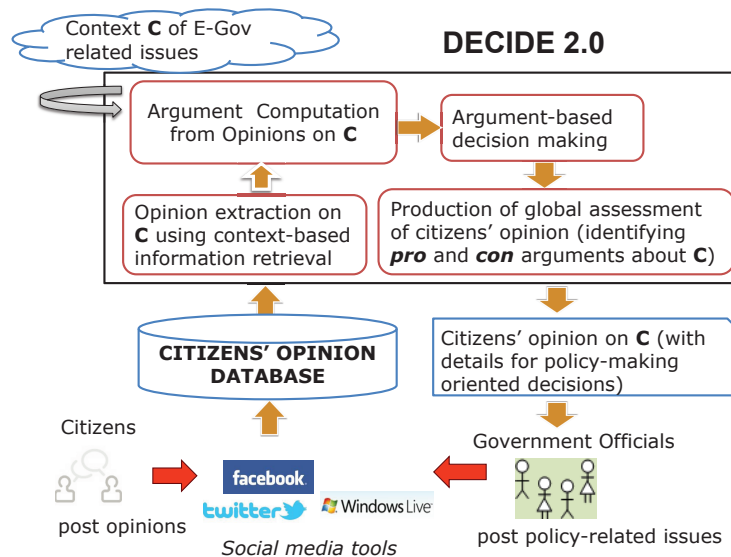


Figure 2: The Decide 2.0 platform: components

- increase transparency –bringing public sector agenda and government activities closer to citizens [4];
- facilitate participation –engaging citizens in making opinion and contributing to policy-decision making; and
- enhance service delivery - pushing service-related information and gathering citizens' opinions about service delivery.

As an example of Government 2.0 adoption, the Government of Singapore offers a directory of the Web 2.0 and other social media initiatives, such as Facebook pages, Flickr photostreams, Twitter accounts, and YouTube channels, among others, used by government agencies [15]. Aware of the benefits and willing to pursue them, governments first need to overcome various types of challenges posted by Government 2.0. In particular, the use of social media requires governments to overcome challenges related to privacy, security, data management, accessibility, social inclusion, governance and policy-related issues [2]. Focusing on the data management perspective, only integrating data streams from social media requires solving two important issues: 1) the magnitude of the information flow associated with such data streams (e.g. Twitter disseminates 55 million tweets a day), and 2) extracting meaningful information –social media data streams are usually incomplete which may be potentially inconsistent, as citizens might have different views on a certain issue.

Addressing technical challenges of data management in government-use social media tools, a framework called DECIDE 2.0 is under development [6], which integrates argumentation technologies and context-based search for intelligent processing of citizens' opinion in social media. The framework relies on text mining and opinion mining techniques to filter noise and detect main topics being discussed by citizens in social media. Recognizing that the use of such techniques is not a common government practice, the main contribution of DECIDE 2.0 is to provide an automated tool for extracting arguments based on citizens' opinions. The framework will enable to assess and confront pro and con arguments to be used by policy makers and government officials as inputs in decision making processes.

DECIDE 2.0 combines context-based search [13] and argumentation [19] in a collaborative system for managing (retrieving and publishing) service- and policy-related information in social media tools used by governments. Therefore, DECIDE 2.0 contributes to a more enhanced set of Government 2.0 tools. DECIDE 2.0 was originally presented in [9] and a revised version of its architecture is presented in Figure 2. The architecture comprises different components: a) Opinion Extraction Module –based on data provided by social media, extracts citizens' opinions on a given theme using context-based search and produces formal predicates, and stores opinions and predicates in a knowledge base; b) Argument Computation Module –takes the collected opinions and models them

as arguments; c) Argument-based Decision Making Module –based on the generated knowledge base, the component selects predicates on a given theme; d) Global Assessment Generator –based on the results of the previous stage, arguments are classified into pro and con and are consolidated into a global assessment of citizens' opinion on a given theme.

Even though DECIDE 2.0 is intended to capture citizens' opinions from different social media, our current research is particularly focused on the use of Twitter and its integration with argumentation. Consequently, in what follows we will outline part of our ongoing research in this direction.

3 Argumentation: an overview

Argumentation is an important aspect of human decision making. In many situations of everyday life, when faced with new information people need to ponder its consequences, in particular when attempting to understand problems and come to a decision. Argumentation systems [19] are increasingly being considered for applications in developing software engineering tools, constituting an important component of multi-agent systems for negotiation, problem solving, and for the fusion of data and knowledge. Such systems implement a dialectical reasoning process by determining whether a proposition follows from certain assumptions, analyzing whether some of those assumptions can be disproved by other assumptions in our premises. In this way, an argumentation system provides valuable help to analyze which assumptions from our knowledge base give rise to inconsistencies and which assumptions are harmless.

In defeasible argumentation, an *argument* is a tentative (defeasible) proof for reaching a conclusion. Arguments may compete, rebutting each other, so a *process* of argumentation is a natural result of the search for arguments. Adjudication of competing arguments must be performed, comparing arguments in order to determine what beliefs are ultimately accepted as *warranted* or *justified*. Preference among conflicting arguments is defined in terms of a *preference criterion* which establishes a partial order " \preceq " among possible arguments; thus, for two arguments A and B in conflict, it may be the case that A is strictly preferred over B ($A \succ B$), that A and B are equally preferred ($A \succeq B$ and $A \preceq B$) or that A and B are not comparable with each other.

For the sake of example, let us consider the well-known example of nonmonotonic reasoning in AI about the flying abilities of birds, recast in argumentative terms. Consider the following sentences: (1) Birds usually fly; (2) Penguins usually do not fly; (3) Penguins are birds. The first two sentences correspond to *defeasible rules* (rules which are subject to possible exceptions). The third sentence is a *strict rule*, where no exceptions are possible. Given now the fact that *Tweety is a penguin* two different arguments can be constructed:

1. Argument A (based on rules 1 & 3): Tweety is a penguin. Penguins are birds. Birds usually fly. So Tweety flies.
2. Argument B (based on rule 2): Tweety is a penguin. Penguins usually do not fly. So Tweety does not fly.

In this particular situation, two arguments arise that cannot be accepted simultaneously (as they reach contradictory conclusions). Note that argument B seems rationally preferable over argument A , as it is based on more *specific* information. As a matter of fact, specificity is commonly adopted as a syntax-based criterion among conflicting arguments, preferring those arguments which are *more informed* or *more direct* [18, 7]. In this particular case, if we adopt specificity as a preference criterion, argument B is justified, whereas A is not (as it is defeated by B). The above situation can easily become much more complex, as an argument may be defeated by a second argument (a defeater), which in turn can be defeated by a third argument, *reinstating* the first one. As a given argument might have many defeaters, the above situation results in a tree-like structure (called *dialectical tree* in [10]), rooted in the first argument at issue, where every argument in a branch (except the root) defeats its parent.

In the next section, we will discuss the difference between dialectical and opinion trees in terms of the different conflict relations among them.

4 Analyzing Twitter from an argumentative perspective

In this Section we will describe how different elements in Twitter can be captured under an argumentative perspective. We will constraint ourselves to the four components introduced in Section 2.

4.1 Logical language for expressing Twitter messages

Twitter messages (Tweets) are 140 character long, with a number of additional fields which help identify relevant information within a message (sender, number of retweets associated with the message, etc.). In particular, we will focus on the presence of *hashtags* (words or phrases prefixed with the symbol #, a form of metadata tag). Hashtags are used within IRC networks to identify groups and topics and in short messages on microblogging social networking services such as Twitter, identi.ca or Google+ (which may be tagged by including one or more with multiple words concatenated). In the sequel we will assume that the term “hashtag” refers to either actual hashtags in Twitter or to relevant keywords found in tweets.

We define a tweet T as a set of terms $\{t_1, t_2, \dots, t_k\}$. We will consider a distinguished subset H of T , where H is a set of hashtags. Let \mathcal{Tweets} be the set of all currently existing tweets.⁵ Given a set of hashtags H , we will write $Tweet_H$ to denote the subset of distinguished elements (tweets) in \mathcal{Tweets} associated with H . In our approach, a query Q is any set of hashtags used for filtering some relevant tweets $Tweet_Q$ from \mathcal{Tweets} . In order to select those tweets relevant for a particular query Q , we will consider an aggregation operator $\text{Agg}_{\mathcal{Tweets}}(Q, C)$ which returns a subset of tweets associated with Q according to some criterion C . This operator could be defined in several ways, e.g. $\text{Agg}_{\mathcal{Tweets}}(Q, C_1) = \{T \in \mathcal{Tweets} \text{ such that } Q \subset T\}$, or $\text{Agg}_{\mathcal{Tweets}}(Q, C_2) = \{T \in \mathcal{Tweets} \text{ such that } Q \subset T \text{ and } T \text{ was retweeted more than 5 times}\}$. Note that for the same query Q , different alternative criteria (C_1, C_2, \dots, C_k) can lead to different distinguished subsets in \mathcal{Tweets} . An example of such a criterion C could be a timestamp, or/and further restrictions, such as only using Tweets from UK, etc.

As explained before, tweets can be associated with different feelings or sentiments. Even if in real life there may be a lot of emotions in tweets (like anger, happiness, and so on), we will assume here that there is only a set \mathbb{S} of three possible sentiments, which are positive, negative and neutral ones (as done for example in platform Sentiment140.com). Thus our assumption is to have a mapping s that maps a set of given tweets into a set \mathbb{S} of three sentiments (i.e. $\mathbb{S} = \{\text{positive}, \text{negative}, \text{neutral}\}$). Note that we are not going into detail on how this is computed, and that we are aware that there may be other ways to rate tweets (such as the number of followers, etc.).

Next we will formalize the previous notions. Let $s : \text{PartsOf}(\mathcal{Tweets}) \rightarrow \mathbb{S}$ be a mapping. We will write $\text{Positive}(\mathcal{Tweets})$, $\text{Negative}(\mathcal{Tweets})$ and $\text{Neutral}(\mathcal{Tweets})$ to denote the set of all possible elements in $\text{PartsOf}(\mathcal{Tweets})$ (subset of tweets) that map via s into \mathbb{S} . We will assume that $\text{Positive}(\mathcal{Tweets}) \cup \text{Negative}(\mathcal{Tweets}) \cup \text{Neutral}(\mathcal{Tweets}) = \mathcal{Tweets}$. We should clarify that the mapping s is intended to take a set of tweets (i.e. an aggregation of tweets) and not an individual tweet to determine its associated prevailing sentiment. We must remark that we are not interested in analyzing a single tweet at a time but all those tweets associated with a given query Q and a given criterion C .

Two sentiments $\text{Sent}_1, \text{Sent}_2 \in \mathbb{S}$ will be called “in conflict” whenever $\text{Sent}_1 \neq \text{Sent}_2$. (e.g. *positive* will be in conflict with *negative*; *neutral* will be in conflict with *negative*). We further assume that all possible conflicts are “equally preferred” in the sense that a conflict between positive and negative is as strong as a conflict between positive and neutral; the underlying idea is to identify when the prevailing sentiments are not the same.

4.2 Twitter-based Arguments. Conflict

Next we will formalize the notion of Twitter-based argument (TB-argument) and Twitter-based argumentation framework. Intuitively, a TB-argument will be provided by three elements: a support (given by a set of distinguished tweets), a conclusion (associated with a given query Q) and a sentiment Sent . A Twitter-based framework will capture the five elements required to formalize TB-arguments (set of possible arguments, attack relationship, aggregation criterion, a search preference criterion, and a set of possible sentiments). Formally:

Definition 4.1. A *Twitter-based argumentation framework* (or just *framework*) is a 5-tuple $(\mathcal{Args}, \text{Attacks}, C, \text{Agg}, \text{Sentiments})$, where \mathcal{Args} is the set of all possible TB-arguments (defined below), Attacks is a partial relation between elements in \mathcal{Args} , Agg is an aggregation operator which selects a subset of elements in \mathcal{Tweets} according to some search preference criterion C for a query Q , and Sentiments is a non-empty set of possible sentiments.

⁵In the analysis that follows, we will assume that the set of all currently existing tweets corresponds to a snapshot of Twitter messages at a given fixed time. It must be noted that the actual Twitter database is highly dynamic.

Definition 4.2. Given a framework $(\mathcal{Args}, Attacks, C, Agg, Sentiments)$, a Twitter-based argument (or just TB-argument) for a conclusion Q is a 3-tuple $\langle Arg, Q, Sent \rangle$, where Arg is $Agg_{\mathcal{Tweets}}(Q, C)$ and $Sent$ is $s(Agg_{\mathcal{Tweets}}(Q, C))$.

Example: Consider a query Q formed by $\{\text{"vote"}\}$, and a criterion C defined as “all $T \in \mathcal{Tweets} \mid \{\text{"obama"}\} \subseteq T$ ”. Then $Arg = Agg_{\mathcal{Tweets}}(Q, C)$ is the set of all possible tweets containing $\{\text{"obama"}, \text{"vote"}\}$. Suppose that $s(Agg_{\mathcal{Tweets}}(Q, C)) = neutral$. Then $\langle Arg, \{\text{"obama"}, \text{"vote"}\}, neutral \rangle$ is a TB-argument.

Definition 4.3. Given a framework $(\mathcal{Args}, Attacks, C, Agg, Sentiments)$, and two queries Q_1 and Q_2 , we will say that Q_1 is strictly more specific than Q_2 whenever $Agg_{\mathcal{Tweets}}(Q_1, C) \subset Agg_{\mathcal{Tweets}}(Q_2, C)$. We will also say that Q_2 subsumes Q_1 .

Example: A query Q_2 formed by $\{\text{"obama"}\}$ subsumes the query Q_1 formed by $\{\text{"obama"}, \text{"president"}\}$, as all tweets that are returned by Q_1 will also be part of Q_2 , but not the other way round.

Definition 4.4. Given a framework $(\mathcal{Args}, Attacks, C, Agg, Sentiments)$, and two arguments $\langle Arg_1, Q_1, Sent_1 \rangle$ and $\langle Arg_2, Q_2, Sent_2 \rangle$ such that Q_2 subsumes Q_1 , we will say that $\langle Arg_1, Q_1, Sent_1 \rangle$ attacks $\langle Arg_2, Q_2, Sent_2 \rangle$ whenever $Sent_1$ and $Sent_2$ are in conflict.

Example: Consider two queries $Q_2 = \{\text{"obama"}\}$ and $Q_1 = \{\text{"obama"}, \text{"president"}\}$, such that:

- $\langle Arg_1, \{\text{"obama"}, \text{"president"}\}, positive \rangle$, and
- $\langle Arg_2, \{\text{"obama"}\}, negative \rangle$.

Then $\langle Arg_1, \{\text{"obama"}, \text{"president"}\}, positive \rangle$ attacks $\langle Arg_2, \{\text{"obama"}\}, negative \rangle$.

5 Opinion trees

In the previous section we have shown how to express arguments for queries associated with a given sentiment. Such arguments might be attacked by other arguments, which on their turn might be attacked, too. In argumentation theory, this leads to the notion of *dialectical tree* [19]. Based on that notion, we will present next the concept of *opinion tree*, which will allow us to take a closer look to tweets found for a certain hashtag.

Assume, for example, that the prevailing sentiment for the query “Obama” is *negative*. A crucial question that arises is whether opinions about Obama are related to other topics, such as political reforms, gossip about him, the election campaign, etc. It might be the case that all *negative* classified tweets are tweets about a specific reform or political decision, while there might be positive opinions associated with his election campaign and other popular reforms.

We have developed an algorithm to explore all possible relationships associated with tweets returned for a query Q and criterion C . The proposed algorithm recursively constructs a tree as follows: The root of the tree is the TB-argument obtained from the original query ($A = Agg_{\mathcal{Tweets}}(Q, C)$). Next, it selects all relevant hashtags from A , which might be used to “extend” Q , by adding a new element (*NewTerm*) to the query, obtaining $Q' = Q \cup \{NewTerm\}$. Then, a new argument for Q' is obtained, which will be associated with a subtree rooted in the original argument A at issue (see high-level algorithm in Fig. 3).

Termination property: For any query Q , the algorithm `GetOpinionTree` finishes in finite time.

Proof: Given that a tweet may not contain more than 140 characters, the number of hashtags in each tweet is finite. In addition, when a new hashtag h is selected from $Agg_{\mathcal{Tweets}}(Q, C)$ to extend Q , the new query becomes $Q' = Q \cup \{h\}$. This new query Q' is a superset of Q and therefore $Agg_{\mathcal{Tweets}}(Q', C) \subseteq Agg_{\mathcal{Tweets}}(Q, C)$. As a consequence the number of hashtags that can be selected from $Agg_{\mathcal{Tweets}}(Q', C)$ will be strictly smaller than the number of hashtags available in $Agg_{\mathcal{Tweets}}(Q, C)$. Note that the number of hashtags in $Agg_{\mathcal{Tweets}}(Q', C)$ is smaller or equal to those in $Agg_{\mathcal{Tweets}}(Q, C)$, but the hashtag h cannot be selected again. Therefore, after a finite number of steps no more hashtags will be available for selection and the algorithm will eventually stop, providing an opinion tree as an output.

ALGORITHM *GetOpinionTree***INPUT:** Query Q , Agg , C **OUTPUT:** Opinion Tree OT_Q $\{ \text{opinion tree rooted in } Q \text{ with aggregation } Agg \text{ under criterion } C \}$ IF $length(Q) \leq 140$ THEN Let $\langle Arg, Q, Sent \rangle$ be the root nodewhere Arg is $Agg_{tweets}(Q, C)$ and $Sent$ is $s(Agg_{tweets}(Q, C))$.IF there are other hashtags in $Agg_{tweets}(Q, C)$ that expand Q

THEN

Compute $L = [h_1, \dots, h_k]$ (list of hashtags that expand Q in $Agg_{tweets}(Q, C)$)

according to some threshold criterion for considering hashtags to be relevant

(e.g. percentage of occurrence within $Agg_{tweets}(Q, C)$)FOR EVERY $h_i \in L$ DOPut $GetOpinionTree(Q \cup \{h_i\}, Agg, C)$ as subtree rooted in $\langle Arg, Q, Sent \rangle$

Figure 3: High-level algorithm for computing opinion trees from Twitter

6 Real-World Examples

This section presents two examples that illustrate how the proposed algorithm can help identify current political trends or trends in citizens' opinions. The presented opinion trees were computed by a prototype of our algorithm that takes advantage of Twitter Search API. This API returns a collection of relevant tweets matching a specified query and therefore the described opinion trees illustrate a (simplified) real-world scenario.

Figure 4 illustrates how the construction of a sample opinion tree for the query "Obama" could look like. The root node corresponds to those tweets found for the original query, which turns out to be negative (-). Suppose that the next query we obtain is "Romney", which is also associated with negative opinions. At this point, we could extend the original query with two terms, namely "Zaman"⁶ and "economic", which are both neutral. If we further analyze our original set (associated with the query "Obama") we could identify new terms that allow us to explore other related topics, such as "vote" (neutral), "unemployment" (negative), "president" (positive), etc. The process could go on further, finding more specific subsets within any of the sets, depending on the collection of retrieved tweets and the threshold settings of the algorithm.

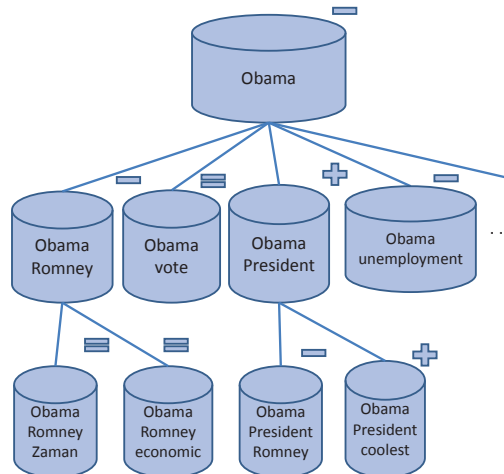


Figure 4: Example of Opinion Tree based on the query "Obama". The tweets were retrieved on October 6, 2012. Some subtrees are left out, therefore this illustration may not precisely reflect the prevailing sentiments.

Our next example deals with Valerie Jarrette, a Senior Advisor to Barack Obama. Jarrette is a highly influencing

⁶A Turkish newspaper (<http://www.zaman.com.tr/>).

advisor at the White House, and several of Obama's decisions were based on her advise. Some examples include Obama's flight to Copenhagen during the health care reform, where he supported the candidature of Chicago for the Olympic Games (the city was rejected in the first round) or the fact that Obama underestimated Romney on the first television debate⁷.

To further test the proposed algorithm, we started with the general query "Jarrette", which turned out to be positive. A deeper analysis of the tweets associated with this query allows us to identify several positive or neutral derived queries, such as "weekend", "miss" or "nice". On the other hand, more specific queries associated with Valerie Jarrette result in negative opinions. These queries include terms such "Valerie" or "Obama" which are good discriminators when trying to focus on the topic of Barack Obama's advisor at the White House. Figure 5 presents the resulting opinion tree.

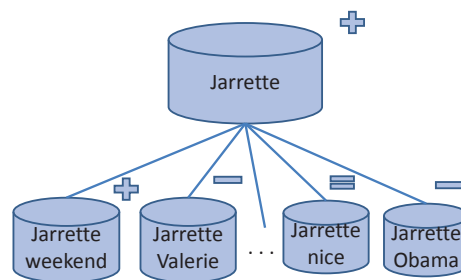


Figure 5: Example of Opinion Tree based on the query "Jarrette". The tweets were retrieved on October 19, 2012.

7 Related Work

Our approach is inspired by recent research in integrating argumentation, social networks and e-democracy. In the last years, there has been growing interest in assessing meaning to streams of data from microblogging services such as Twitter, as well as research in using argumentation in e-government contexts. In [5], Cartwright et al. presented different issues related to exploiting argument representation in systems for e-democracy. In particular, the authors discuss the contributions of the *Parmenides* software tool, which is intended as a system for deliberative democracy whereby the government is able to present policy proposals to the public so that users can submit their opinions on the justification presented for the particular policy. In contrast with our approach, this research work assumes that argument schemas are established beforehand, and are not detected as emerging patterns from social network activities. Torroni & Toni [21] coined the term *bottom-up argumentation*, as they take a grass-root approach to the problem of deploying computational argumentation in online systems. In this novel view, argumentation frameworks are obtained bottom-up starting from the users' comments, opinions and suggested links, with no top-down intervention of or interpretation by "argumentation engineers". As the authors point out "topics emerge, bottom-up, during the underlying process, possibly serendipitously". We generalize this view by identifying two issues: on the one hand, a metalevel characterization of rule-based argument processes, based on social network knowledge bases. On the other hand, we distinguish schema-based argumentation as an alternative for bottom-up argumentation, also obtained in a similar way as for rule-based argumentation. In [11], Heras et al. show how the theory of argumentation schemes can provide a valuable help to formalize and structure on-line discussions and user opinions in decision support and business oriented websites that hold social networks among their users. In their investigation real case studies are considered and analyzed, establishing as well guidelines for website and system design to enhance social decision support and recommendations with argumentation. Their research pinpoints several issues presented in our approach, but does not aim at a particular applicability for e-government issues, nor for identifying emerging patterns in network traffic and associating them with high-level arguments. In [12], Klein & Iandoli describe *Collaboratorium*, a system that enables collaborative deliberation where users can create networks of posts organized as an argument map. In this sense, this system resembles our proposal in that it adopts knowledge sharing technologies to facilitate logic-based knowledge organization.

⁷Source SPIEGEL 42/2012, pages 102/103 (<http://www.spiegel.de/international>)

However, differently from our proposal, it is not intended to mine social media to automatically identify conflicting positions but to support large-scale argumentation, where users are allowed to enter arguments and a moderator takes a key role. Finally, in [1], Abbas & Sawamura formalize argument mining from the perspective of intelligent tutoring systems. In contrast with our approach, they rely on a relational database, and their aim is not related with identifying arguments underlying social networks as done in this paper.

8 Conclusions and Future Work

In this paper we have presented a first approach towards integrating argumentation and microblogging technologies, with a particular focus on Twitter. We have shown how the different elements in argumentation theory can be conceptualized in terms of Twitter messages, according to relevant fields present in those messages (number of retweets, provenance, etc.). We have also presented a definition of argument that considers as a support the bunch of Tweets which are associated with a particular set of terms (hashtags). For such an argument, we also define a polarity (positive, negative, neutral), obtained in terms of sentiment analysis tools. Such polarity allowed us to characterize the notion of conflict between arguments, establishing as well as the backgrounds for formalizing defeat. We showed how this idea could be exploited in terms of so-called “opinion trees”, which resemble argumentative dialectical trees. Their aim, in contrast, is to explore the space of possible confronting opinions associated with a given opinion, in terms of the specificity principle used in argumentation for preferring arguments.

Part of our future work is associated with deploying the ideas presented in this paper in a software product. As a basis for such deployment, visual tools for displaying and analyzing dialectical trees have been already developed for Defeasible Logic Programming. We expect to use the underlying algorithms from this tool in our framework. Additionally, we expect to perform different experiments with hashtags associated with relevant topics, assessing the applicability of our approach in a real-world context. In addition, there exists also the possibility of not only expanding hashtags of one set of tweets, but always looking for all tweets given a new hashtag. Thus not a tree but a graph would be built up, and connections between different topics (hashtags) become clear. This would give us the advantage of being able to observe if a special hashtag is positive/negative only together with some other hashtags or by itself (leaving apart indicator words such as “good”, “bad”, etc.). Research in this direction is currently being pursued.

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