Empowering Citizens through Opinion Mining from Twitter-based Arguments

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ABSTRACT
Several participation initiatives are been conducted by many governments around the world, following the open government trend. Despite of the wide range and variety of such initiatives, most of them face a common technical challenge: lack of appropriate technical tools to automatically summarize stakeholders' opinions and discussions. This paper focuses on some recent contributions within a recent e-Participation framework, namely Electronic Empowerment (E^2) Participation. This concept was coined as part of a multi-disciplinary research project, aiming at integrating Artificial Intelligence and Software Engineering techniques and tools with Electronic Governance models and principles to design innovative tools for e-Participation. The main contribution of this ongoing research paper is an outline of a novel algorithmic characterization for opinion mining, which is being developed within the E^2 framework.

Categories and Subject Descriptors
J.1 [**Administrative Data Processing**]: Government; I.2 **[Artificial Intelligence]**: Learning; H.3 **[Information Storage and Retrieval]**: Information Search and Retrieval

General Terms
Algorithms, Design, Human Factors, Languages

Keywords
E-participation; Electronic Governance; Argumentation; Agreement Technologies; Social Media

1. INTRODUCTION AND MOTIVATIONS
Most e-Participation initiatives nowadays take place within ad-hoc platforms which provide suitable channels for efficient electronic communication and coordination connecting the involved stakeholders (e.g. citizen-government, business-government, partner-business, etc.). Nevertheless, such platforms do not provide suitable and generic components to model and process emerging *collective thinking patterns* in communities (particularly through the widespread use of social media and their support by mobile technologies). Collective thinking patterns could correspond to ideas, proposals, criticisms or viewpoints, which decision makers can identify and confront based on atomic, individual inputs from citizens and users, such as tweets, Facebook posts, web-based product reviews, etc. Such patterns can take place in different contexts associated with social innovation and change, e.g. crowdfunding initiatives, opinion mining, citizen journalism, cyberactivism, etc.

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Electronic Empowerment Participation (E^2P) [3] captures a radically new perspective on e-Participation, where collective thinking patterns can be identified under the generic form of *"arguments"*, being contrasted automatically, enhancing thus the abilities of the different stakeholders to engage in creative participatory processes. The underlying machinery that makes E^2P possible is given by agreement technologies [3], a new metaphor that integrates several aspects from database theory, artificial intelligence, multi-agent systems and social infrastructures.

This ongoing research paper summarizes some of the main advances on the algorithmic characterization of the argumentation mechanisms used during the opinion mining process. In particular, we will provide some results obtained through the analysis of Twitter as a social media tool.

2. THE E^2P FRAMEWORK: OVERVIEW
The E^2P framework relies on social media platforms as a generic communication platform, incorporating novel algorithms for performing intelligent aggregation and reasoning from the inputs of individual citizens and users in order to identify collective thinking patterns to assist in particular government-decision- and policy- makers in understanding public opinion. In particular, three main technologies are involved: 1) *Argumentation mechanisms* [6], which will help assess which arguments in online interactions and discussions have stronger grounds; 2) *Trust and reputation models* [2], which will be coupled with the argumentation mechanism to help assess the reliability of information and information sources; and (3) *Natural language processing*, which will be used in structuring online information by building argumentation graphs which provide the needed bases for argumentation mechanisms. The above three technologies will add structure to online information by linking scattered and unorganized information into coherent discussions; noise resulting from redundancy will be reduced through grouping related information together ; noise resulting from spam, lies and bias will be reduced by assessing the reliability of information.

The E^2P Framework comprises a knowledge base storing users' opinions (UOK) and 6 major software components: 1) *NLP Component* – provides various Natural Language Processing (NLP) tools to extract terms, relations and entities, to parse text and do semantic annotation and semantic analysis;

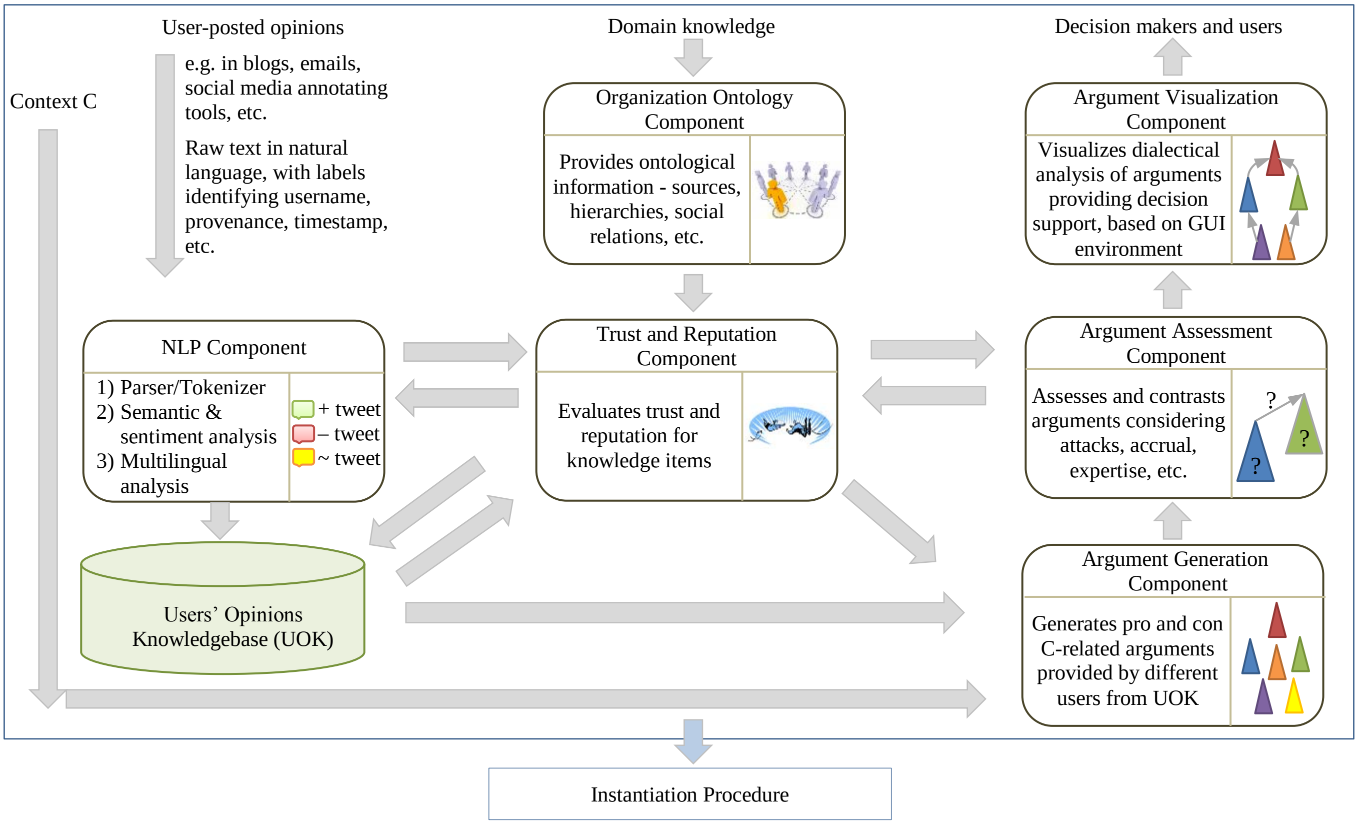

Figure 1: The E^2 Participation Framework

2) *Argument Generation Component* – given a context C for analyzing opinions, the component generates pro and con arguments based on the opinions stored in UOK; 3) *Organization Ontology Component* – provides an ontology defining domain knowledge, such as information sources, concept hierarchies, social relations, etc.; 4) *Trust and Reputation Component* – implements a trust and reputation system to weight arguments based on provenance and domain knowledge; 5) *Argument Assessment Component* – based on the status assigned to individual arguments, assesses and contrasts arguments considering various criteria, like attacked argument, accrual, user expertise; and 6) *Argument Visualization Component* – based on graphic user interfaces (GUI), the component enables to visualize dialectical analysis of arguments to support and facilitate decision-makers' tasks. In addition, the E^2P framework includes an *Instantiation Procedure* providing guidelines to instantiate the framework for a given use case.

3. GENERATION

In this section we will summarize some of the major elements under consideration in E^2P for formalizing argument construction and assessment (elements 2 and 3), in particular when analyzing a particular, restricted form of input, namely *tweets* provided by users in a certain context.

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 descriptors which are either hashtags (words or phrases prefixed with the symbol #, a form of metadata tag) or terms that tend to occur often in the context of a given topic. Consider for example the issue "abortion". Some tweets on that topic could be as follows:

Tweet1="government should ban #abortion, it means killing babies"

Tweet2 = "#abortion is debatable, not all cases are to be equally considered"

Tweet3="#abortion is a right every woman has. Defend it"

Tweet4= …

We will assume that a tweet is just a "bag" of words, not taking into account the actual order of terms in the tweet. Additionally, we assume that the set of all currently existing tweets corresponds to a snapshot of Twitter messages at a given fixed time, as the Twitter database (i.e., the universe of tweets within a certain time frame) is highly dynamic. In our approach, a **query** Q is any set of descriptors used for filtering some relevant tweets from the set of existing tweets based on a given criterion C. In order to abstract away how such selection is performed, we will define an **aggregation operator** Agg(Q,C). There are several alternative definitions for Agg(Q,C). For instance, suppose that C1 is a criterion that indicates that only tweets posted between timestamp T1 and T2 are to be selected. Then Agg(Q,C1) will select only those tweets that contain all the terms of query Q and have been posted in the time period [T1,T2]. Other examples of criteria that can be naturally applied are, for instance, requiring that those tweets were retweeted more than n times, requiring that every user that posted tweets T has at least m followers, etc. Finally, we will also assume a set S of possible **sentiments.** A possible range for S could be *positive*, *negative* and *neutral* (as done for example in commercial platform sentiment140.com; in this platform, prevailing sentiments associated with a tweet set are expressed by percentages). For the sake of example, Tweet1 could be considered as a negative tweet towards abortion, whereas Tweet3 corresponds to a positive tweet on that topic.

We will generalize the notion of sentiment associated with a single tweet to the notion of *prevailing sentiment* in a bunch of tweets (i.e., the sentiment that prevails, according to some criterion, e.g. percentage). In the same way, we will assume that sentiments might convey conflicting feelings or emotions (e.g. anger vs. happiness; boredom vs. excitement, positive vs. negative, etc.). We will abstract away which is the prevailing sentiment as well as existing conflicts through mapping functions *Sent* and *Conflict*, respectively.

3.1 Formalizing a Twitter-based Framework and Twitter-based Arguments

The preceding elements provide the background required to define a Twitter-Based (TB) Argumentation Framework, and the notion of TB-argument (or TB-opinion).

A **TB-argumentation framework** is a 5-tuple *(Tweets, C, S, Sent, Conflict)*, where *Tweets* is the set of available tweets, *C* is a selection criterion, *S* is a non-empty set of possible sentiments and *Sent* and *Conflict* are sentiment prevailing and conflict mappings. A **TB-argument** for a query Q is a 3-uple <Arg, Q, *Sent*>, where

- Arg corresponds to a bunch of tweets associated with a query Q, obtained through Agg(Q,C)
- *Sent* is the prevailing sentiment associated with Agg(Q,C)

Example: Consider a TB-framework *(Tweets, C, S, Sent, Conflict*), where Q = {“abortion",”murder"}, *C* is defined as all tweets after Jan 1, 2012, and *S* = {pos, neg, neutral}, such that: *Conflict*(pos) ={ neg, neutral}, *Conflict*(neg) ={pos, neutral} and *Conflict*(neutral) ={ pos,neg}. Then Arg = Agg(Q,C) is the set of all possible tweets containing {“abortion", “murder"} that have been published since Jan. 1, 2012. Suppose that *Sent*(AggTweets(Q,C)) = negative (i.e., the prevailing sentiment involved is negative). Then <Arg; {“abortion",”murder"},negative> is a TB-argument.

3.2 Contrasting Arguments & Counter-arguments: Opinion Trees

We have shown how to express arguments for queries associated with a given prevailing sentiment. Such arguments might be *attacked* by other arguments, which on their turn might be attacked, too. In argumentation theory [8], this leads to the notion of *dialectical analysis*, which can be associated with a tree-like structure in which arguments, counter-arguments, counter-counter-arguments, and so on, are taken into account. The central idea underlying the exploration of possible attacks for a given argument is given by the notion of *specificity*.

Suppose that a TB-argument supporting the query Q=“abortion" is obtained, with a prevailing *negative* sentiment. If the original query Q is extended in some way into a new query Q’ that is more specific than Q (i.e. Q’ = Q ∪ {d}, for some descriptor d), it could be the case that a TB-argument supporting Q’ has a different (possibly conflicting) prevailing sentiment. For example, more specific opinions about abortion are related to other topics, like for example ethics, social problems or programs, religious issues, etc. To explore all possible relationships associated with TB-arguments returned for a specified query Q and criteria C, we can define an algorithm to construct an *opinion tree* recursively as follows:

Algorithm BuildOpinionTree

Input: Q

Output: Opinion Tree rooted in <Arg, Q, Sent>

1. We start with a TB-argument A obtained from the original query Q (i.e., <Arg,Q,Sent>), which will be the root of the tree.

2. Next, we compute within A all relevant descriptors that might be used to “extend” Q, by adding a new element (NewTerm) to the query, obtaining Q’ = Q ∪ {NewTerm}.

3. Then, a new argument for Q’ is obtained, which will be associated with a subtree rooted in the original argument A (i.e., the tree resulting from BuildOpinionTree(Q’)).

It is also easy to see that for any query Q, the algorithm BuildOpinionTree finishes in finite time: given that a tweet may not contain more than 140 characters, the number of contained descriptors is finite, and therefore the algorithm will eventually stop, providing an opinion tree as an output.

4. CASE STUDY: THE ABORTION ISSUE

Next we show a case study based on the abortion issue, obtained from Twitter in December 2012, when Michigan legislature was debating several regulations on abortion practices.

Consider the query Q = “abortion", and a criterion C = {tweets posted less than 48 hours ago}. A root TB-argument is computed for Q and C, obtaining an associated prevailing sentiment (negative). It should be remarked that the algorithm for building opinion trees avoids the repetition of any new descriptor used to extend the query associated with a node. The construction is performed depth-first, so that new descriptors are gradually introduced using a technique specifically designed to guide term selection (outside the scope of this paper).

Figure 2 illustrates how the construction of an opinion tree for the query Q = “abortion" looks like. Distinguished symbols (+, -, =) are used to denote positive, negative and neutral sentiments, respectively. Note that the original query Q has cardinality 1, and further levels in the opinion tree refer to incrementally extended queries (e.g. {“abortion", “michigan"}, or {“abortion", “murder"}). Leaves correspond to arguments associated with a query Q’ which cannot be further expanded, as the associated number of tweets is too small for any possible query Q’ ∪ {*d*}, for some *d*. Furthermore, we can identify some subtrees in the Opinion Tree rooted in “abortion” which consist of nodes having all the same sentiment.

In other words, further expanding a query into more complex queries does not change the prevailing sentiment associated with the root node. In other cases, expanding some queries results in a sentiment change (e.g. from “abortion" into {“abortion", “option"} or {“abortion", “wish"}). This situation will allow us to characterize so-called conflict trees, which are outside of the scope of this paper [7].

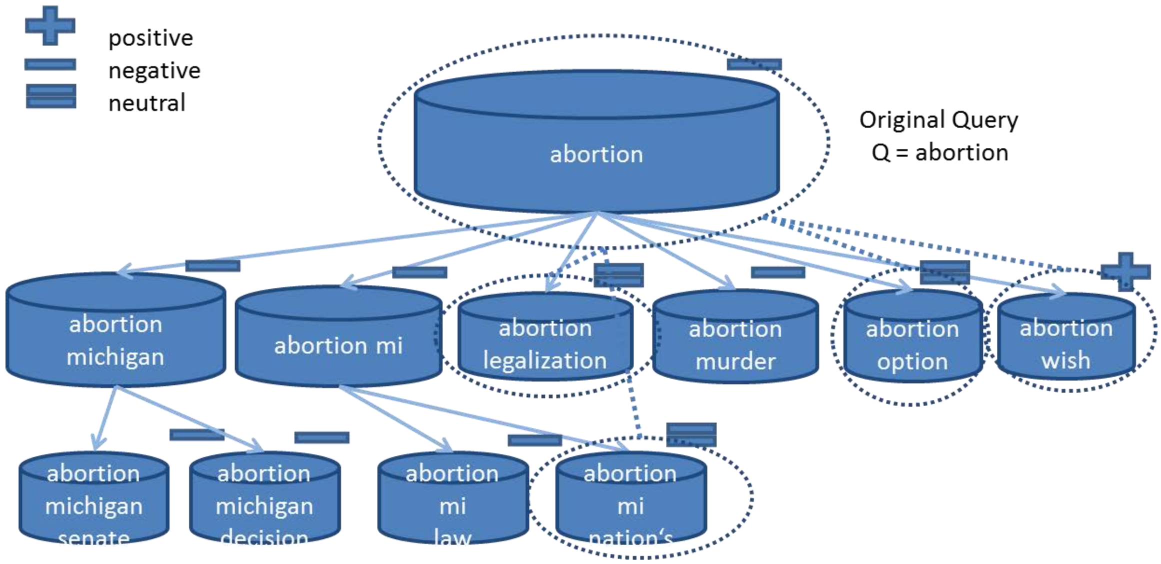

Figure 2: An Opinion Tree for The Abortion Issue

5. CONCLUSIONS, FUTURE WORK

In this paper we have presented some ongoing research concerning the formalization of arguments in the context of the E^2P framework. Even though our formalization and algorithmic approach has been defined for Twitter, it can be generalized to other input sources. Part of our current work involves incorporating additional ontological elements (e.g. assessing the reputation of the users involved), in order to extend the current formalization to encompass more general use cases [7]. Our research is also oriented towards combining argumentation in different settings, in which online consultation might be significant (see e.g.[5]). Finally, the mathematical characterization of opinion trees and their properties is also an interesting subject of study (particularly oriented towards speeding up the construction of opinion trees). Research in these directions is currently underway.

6. ACKNOWLEDGMENTS

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7. REFERENCES

[1] C. Chesñevar, A. Maguitman, E. Estévez, and R. Brena. Integrating Argumentation Technologies and Context-Based Search for Intelligent Processing of Citizens' Opinion in Social Media. In Proc. ICEGOV 2012, Albany, NY, USA, October 2012, pp. 171-174, 2012.

[2] N. Osman, C. Sierra, F. McNeill, J. Pane, and J. Debenham. Trust and Matching Algorithms for Selecting Suitable Agents, ACM Transactions on Intelligent Systems and Technology 5(1): 16 (2013).

[3] C. Chesñevar, A. Maguitman, E. Estevez, N. Osman, C. Sierra: E^2 participation: electronically empowering citizens for social innovation through agreement technologies. DG.O 2013: 279-280

[4] S. Ossowski (ed.). Handbook of Agreement Technologies, volume 8 of Law, Governance and Technology, Springer, New York, January 2013.

[5] F.Steibel, E. Estevez: Designing argumentative metrics for online consultation portals in Brazil. DG.O 2012: 272-273

[6] Argumentation in Artificial Intelligence. I.Rahwan, G.Simari (Eds.). Springer, 2009.

[7] K. Grosse, M. González, C. Chesñevar, A. Maguitman Integrating Argumentation and Sentiment Analysis for Mining Opinions from Twitter . In AI Communications, IOS Press (in press), 2014.

[8] Toulmin, S. (1959). The uses of argument. Cambridge: Cambridge University Press.