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Chapter Title:
Opinion Aggregation and Conflict Resolution in E-Government Platforms
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Contrasting Social Media Information through Argumentation

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1. Introduction and Motivations

At the dawn of the United Nations (UN) Agenda for Post 2015 (UN General Assembly, 2014), governments around the world have already recognized that the current development paths are unsustainable and that new governance mechanisms need to be envisioned to promote sustainable development - sustained and inclusive economic growth, social development and environmental protection. In particular, one of the major governance goals for achieving sustainable development is to develop more fair, equitable and inclusive societies, where the voice and needs of all stakeholders are heard and considered. For this reason, stakeholder engagement is at the core of most government initiatives in the post-2015 age.

The voice and needs of government stakeholders are usually contradictory, since they usually represent opposed interest from different groups - e.g. on the one hand, businesses are interested in pursuing economic development, while on the other hand, environmentalists are concerned with protecting natural resources against blind economic interests. Developing new governance mechanisms contributing to bridge differences among stakeholders' needs post various types of challenges - technical, political, organizational, etc; that governments need to overcome. At the same time, Information and Communication Technologies (ICTs) offer new and innovative solutions that governments can adopt to resolve some of such technical and governance-related challenges.

Within the scenario described above, a fundamental need for policy makers and government decision makers is to back their decisions and agreements on arguments and 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, new ITCs used by citizens in their daily lives, like Facebook and Twitter provide a unique opportunity for governments to leverage on technologies already infused and adopted by the society, providing a knowledge base from which information could be collected and analyzed in order to provide inputs and partially automatize government decision making processes. In particular, tweets have a rich structure, providing a number of record fields which allow to detect provenance of the tweet (author), number of re-tweets, followers, etc.

Aware about the need for citizen participation, governments at different levels - national, regional and local, in most countries are seeking their participation through the use of ICTs (Electronic Participation or e-Participation). 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. government-citizens, government-business, citizens-citizens, partner-business, etc.). Nevertheless, such platforms do not provide suitable and generic components to model and process emerging **collective thinking patterns** in communities; although understanding such patterns is a mainstream trend nowadays in daily life, 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 policy contexts associated with social innovation and change, e.g. crowdfunding initiatives, citizen journalism, cyberactivism, etc.

Government 2.0 refers to government's adoption of Web 2.0 technologies to socialize government services, processes, and data, improving relationships between government and the governed. Enabling new communication channels - such as social media, wikis, blogs, and others; and two-way communication - enabling to push and pull information to and from citizens; Government 2.0 provides new mechanisms for government agencies to: 1) increase transparency –bringing public sector agenda and government activities closer to citizens; 2) facilitate participation –engaging citizens in government decision- and policy-making processes; and 3) enhance service delivery –pushing service-related information and gathering citizens’ opinions about service delivery to design customer-oriented public services that better serve their needs.

To materialize the benefits promised by Government 2.0, public institutions must resolve several issues related to privacy, security, data management, accessibility, digital divide, governance and policy, among many others. Focusing on the data management perspective, the aggregation of information from data streams in social media tools (such as Facebook or Twitter) 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) the extraction of meaningful information and the determination of potential conflicting views (viewpoints emerging from social media data streams are usually in conflict, as citizens might have different views on a certain issue).

In this context, over the last few years **argumentation systems** (Rawhan, & Simari, 2009; García, & Simari, 2004; Besnard, & Hunter, 2008; Modgil et al, 2012) have been gaining increasing importance in several areas of Artificial Intelligence, mainly as a vehicle for facilitating rationally justifiable decision making when handling incomplete and potentially inconsistent information. Argumentation provides a sound model for dialectical reasoning, which underlies discussions or opinion confrontation in social networks. Argumentation systems 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 are really giving rise to inconsistency and which assumptions are harmless.

The underlying idea of applying argumentation systems for mining citizens' opinions on a given topic is the following. Given a topic, we will model the notion of opinion supporting it as a collection of atomic opinions, which can be aggregated according to certain specific criteria. Based on topic specificity and preferences defined on different dimensions or features, opinions can be contrasted with counter-opinions, which have to be preferred (according to a partial order) with respect to the opinion at issue. As a result, we will be able to obtain an "opinion analysis tree", rooted in the first original topic. Distinguished, conflicting elements in an opinion tree lead to so-called "conflict opinion analysis trees", which resemble dialectical trees as those used traditionally in argumentation theory. In our analysis, we distinguish a particular function for abstracting away the "sentiment" associated with a particular piece of information. Different sentiments can be established as a reference value (e.g. anger, joy, etc.), in a modular way independent from the general framework. By aggregating single pieces of information the general sentiment of the emerging "opinion" can be established. Every opinion is rooted in a particular set of keywords, which is expanded into larger sets in order to get possible counter-opinions, counter-counter-opinions, and so on. We also provide theoretical results which account for an algebraic characterization of our proposal, using equivalence classes to minimize the representation space to be analyzed when contrasting arguments. As a case study, we will present different real-world examples from Twitter, showing the emerging argument-based characterization obtained from our proposal, based on a prototypical implementation of the underlying algorithm in Java.

This book chapter presents an account of recent advances in the development of a novel e-participation framework which integrates social networks (particularly Twitter), intelligent information retrieval and argumentation techniques. This research started within the LACCIR Project DECIDE 2.0 (funded by Microsoft Research Latin America and the Inter-American Development Bank), which aims at integrating Artificial Intelligence and Software Engineering techniques and tools with Electronic Governance models and principles to design innovative tools for conflict resolution in e-Government contexts. We discuss a novel conceptualization for Electronic Empowerment Participation (E^2P), a radically new perspective on e-Participation, where collective thinking patterns can be identified under the generic form of "arguments", being contrasted automatically and 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, a new metaphor that integrates several aspects from database theory, artificial intelligence, multi-agent systems and social infrastructures. A core component in this conceptualization is an underlying argument-based approach, which allows to mine opinions from text-based information items based on incrementally generated topics.

Following this introduction, the rest of this chapter is structured as follows. Section 2 explains the fundamentals about argumentation technologies. Section 3 presents the proposed E^2P framework. Section 4 introduces the algorithms implemented in the E^2P framework tools, and Section 5 illustrates the application of the tools in two case studies. Finally, Section 6 discusses related work, while Section 7 draws some conclusions and future work.

2. Argumentation Technologies - Fundamentals

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 (Rawhan & Simari, 2009; García & Simari, 2004; Besnard & Hunter, 2008) 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 "$\preccurlyeq$" 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 ($A \succcurlyeq B$ and $A \preccurlyeq B$) 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* (Besnard & Hunter, 2008) . 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, rooted in the first argument at issue, where every argument in a branch (except the root) defeats its parent.

Over the last few years, argumentation has been gaining increasing importance as a vehicle for facilitating "rational interaction" (i.e., interaction which involves the giving and receiving of reasons). This is because argumentation provides tools for designing, implementing and analysing sophisticated forms of interaction among rational agents. Argumentation has made solid contributions to the practice of multi-agent dialogues, and its application domains include: legal disputes, business negotiation, labor disputes, team formation, scientific inquiry, deliberative democracy, ontology reconciliation, risk analysis, scheduling, and logistics. A single agent may also use argumentation techniques to perform its individual reasoning because it needs to make decisions under complex preferences policies, in a highly dynamic environment.

In this context, different opinion groups may emerge, using online conversations and social media to coordinate and support decision-making. A fundamental need is to identify possible claims and the information provided to support them, as well as the user communities which are arguing pro and against different issues, within particular constraints (time, geographical location, etc.). This will lead to the generic characterization of collective thinking patterns as arguments, which will be presented in the next sections, providing a central component for the inference machinery used in the E2P framework.

3. The E^{2}P framework

Electronic Empowerment Participation (E^{2}P) (Chesñevar et al, 2013; Chesñevar et al, 2014) 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 E2P possible is given by agreement technologies (Ossowski, 2013), a new metaphor that integrates several aspects from database theory, artificial intelligence, multi-agent systems and social infrastructures.

Figure 1: The E^2 Participation Framework

The E^{2}P 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^{2}P 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; 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 weigh 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^{2}P framework includes an *Instantiation Procedure* providing guidelines to instantiate the framework for a given use case.

As can be seen from Figure 1, the E^{2}P framework encompasses many components, many of which are currently under development. In line with the focus of this chapter concerning opinion aggregation and conflict resolution in e-government platforms, we will focus on the conceptualization of the Argument

Generation Component and the Argument Assessment Component, using Twitter as underlying social network.

4. Opinion Trees in E^2P: contrasting viewpoints and sentiments

In this section we will summarize some of the major elements under consideration in E^2P for formalizing argument construction and assessment, 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:

$Tweet_1$=”government should ban #abortion, it means killing babies”

$Twee_{t2}$ = “#abortion is debatable, not all cases are to be equally considered”

$Tweet_3$=”#abortion is a right every woman has. Defend it”

$Tweet_4$= …

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 C_1 is a criterion that indicates that only tweets posted between timestamp T_1 and T_2 are to be selected. Then Agg(Q,C_1) will select only those tweets that contain all the terms of query Q and have been posted in the time period [T_1,T_2]. 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, $Tweet_1$ 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.

Logical Language for Expressing Twitter Messages

Twitter messages (Tweets) are 140 character long, with a number of additional fields (metadata) 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. Stopwords (such as “a”, “this”, “and”, etc.) will not be considered descriptors and will be ignored in our analysis. 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). Other good descriptors can be dynamically found by looking for terms that are frequently used in tweets related to the topic at hand. In the sequel we will assume that the term “descriptor” refers to either actual hashtags in Twitter or to relevant keywords found in tweets.

We define a tweet *T* as a bag (or multiset) of descriptors $\{d_1, d_2, . . . d_k\}$. We will consider a distinguished subset *Q* of *T*, where *Q* is a set of descriptors and will be denoted query. Let Tweets be the set of all currently existing tweets. Given a query Q, we will write $Tweet_Q$ to denote the subset of distinguished elements (tweets) in Tweets associated with *Q*. In our approach, a query *Q* is any set of descriptors used for filtering relevant tweets $Tweet_Q$ from Tweets. In order to select those tweets relevant for a particular query *Q*, we will consider an aggregation operator Agg(*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. $\mathrm{Agg}(Q,C_1) = \{ T \in \mathrm{Tweets}$ such that $Q \subseteq T \}$, or $\mathrm{Agg}(Q,C_2) = \{ T \in \mathrm{Tweets}$ such that $Q \subseteq T$ and *T* was retweeted more than 5 times $\}$. Note that for the same query *Q*, different alternative criteria (C_1, C_2, . . . , C_k) can lead to different distinguished subsets in 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 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 a have a mapping *s* that maps a set of given tweets into a set S of three sentiments (i.e. S = *{positive*, *negative*, *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 $s: 2^{\mathrm{Tweets}} \rightarrow S$ be a mapping. We should clarify that the mapping *s* is indented 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 $Sent_1; Sent_2 \in S$ will be “in conflict” whenever $Sent_1 \neq Sent_2$. (e.g. *positive* will be in conflict with *negative*; *neutral* will be in conflict with *negative*). According to this, we can say that a set of tweets $\mathrm{Tweets}_1 \subseteq \mathrm{Tweets}$ is in conflict with a set of tweets $\mathrm{Tweets}_2 \subseteq \mathrm{Tweets}$ whenever $s(\mathrm{Tweets}_1) \neq s(\mathrm{Tweets}_2)$. 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.

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), as discussed before.

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.

Contrasting Arguments and Counter-arguments: Opinion Trees and Conflict 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 (Rahwan&Simari, 2009), 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 U {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 OT_Q 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 (d) to the query, obtaining Q' = Q U {d}.

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.

Given an opinion tree we might be interested in finding a minimal structure that reflects all existing conflicts between opinions it the tree. In other words, we might want to build a minimal tree such that arguments and counter-arguments are easy to visualize. To accomplish this, we apply a partitioning algorithm to generate a minimal structure that preserves the conflicts between arguments existing in the original opinion tree. The application of this algorithm results in a natural grouping of arguments that are related to and no conflicting with each other, forming equivalence classes of arguments. The resulting minimal structure also has a tree structure and we will refer to it as *conflict tree*. The notion of lowest common ancestor (LCA) of two nodes in a tree is used to compute a conflict tree. The LCA of two nodes n_1 and n_2 in a tree is the lowest (most specific) node that has both nodes n_1 and n_2 as descendants. The following algorithm describes the steps involved in the transformation of an opinion tree (OT_Q) into a conflict tree (CT_Q):

Algorithm BuildConflictTree
Output: Conflict Tree CT_Q

1. For each pair of TB-arguments $\langle Arg_i, Q_i, Sent_i\rangle$ and $\langle Arg_j, Qj, Sent_j\rangle$ in

the Opinion Tree OT_Q, we define the $\sim_0$ equivalence relation as follows:

$\langle Arg_i, Q_i, Sent_i\rangle \sim_0 \langle Arg_j, Qj, Sent_j\rangle$ if and only if $Sent_i = Sent_j$

2. n = 0; compute the 0-equivalence classes based on the $\sim_0$ equivalence relation

3. REPEAT

    n = n + 1

    Compute the n-equivalence classes as a refinement of the (n − 1)-equivalence classes:

    $\langle Arg_i, Q_i, Sent_i\rangle \sim_n \langle Arg_j, Qj, Sent_j\rangle$ if and only if

    (1) $\langle Arg_i, Q_i, Sent_i\rangle \sim_{(n-1)} \langle Arg_j, Qj, Sent_j\rangle$, and

    (2) For all $\langle Arg_k, Q_k, Sent_k\rangle$ in OT_Q

    $LCA(\langle Arg_i, Q_i, Sent_i\rangle, \langle Arg_k, Q_k, Sent_k\rangle) \sim_{(n-1)} LCA(\langle Arg_j, Qj, Sent_j\rangle, \langle Arg_k, Q_k, Sent_k\rangle)$

  UNTIL the n-equivalence classes are equal to the (n − 1)-equivalence classes

4. Define CT_Q by taking exactly one element from each of the equivalence classes defined for OT_Q .

5. RETURN CT_Q

To illustrate this algorithm, consider the opinion tree presented on the left-hand side of Figure 2. In this figure, we use the label Q_i as a shorthand for $\langle Arg_i, Q_i, Sent_i\rangle$. The partitioning algorithm BuildConflictTree will identify eight equivalence classes: $\{Q_1,Q_2,Q_3,Q_8,Q_{10},Q_{11},Q_{12},Q_{13},Q_{14},Q_{19}\}$, $\{Q_4,Q_6,Q_7\}$, $\{Q_5\}$, $\{Q_9\}$, $\{Q_{15},Q_{16},Q_{17}\}$, $\{Q_{18}\}$, $\{Q_{20},Q_{22}\}$ and $\{Q_{21}\}$. By taking exactly one element from each equivalence class, we obtain the conflict tree depicted on the right-hand side of Figure 2.

Figure 2: From an opinion tree to a conflict tree

5. Two application cases: the Abortion issue and User Segmentation

Next we show how the proposed approach can be used to handle two different case studies: the abortion issue (based on tweets related to that topic in December 2012), and the user segmentation problem.

5.1. The Abortion Issue

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, for a detailed description see (Gosse, González, Chesñevar, & Maguitman, 2015)).

Figure 3 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 augmented 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’ U {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"}).

Figure 3: An Opinion Tree for The Abortion Issue (computed from Twitter, 2012).

Figure 4: Conflict Tree derived from the Opinion Tree for The Abortion Issue

Following the BuildConflictTree algorithm it is possible to derive a minimal structure (conflict tree) where conflicts among opinions are readily available for analysis.The conflict tree resulting from applying the BuildConflictTree algorithm to the opinion tree of Figure 3 is presented in Figure 4. Note that the resulting conflict tree only contains a representative element from each equivalence class of queries. Therefore, immediate descendants of a node will necessarily have a different polarity from that of their parent. This results in a tree that resembles dialectical trees as those used traditionally in argumentation.

5.1. The User Segmentation Problem

The abortion issue example sketched the use of the E^2P framework in a real case when both the query Q and the criteria C were previously stated. However, in many cases even if the query Q is clearly known, the challenge is related to the specification of some accurate criterion C.

A relevant example is the practice of audience segmentation when studying user's behavior in the current e-scenario from a User Centered Design (UCD) perspective. UCD is a broad term to describe design processes in which end-users influence how a design takes shape. It is both a broad philosophy and variety of methods. There is a spectrum of ways in which users are involved in UCD but the important concept is that users are involved one way or another (Abras, C., Maloney-Krichmar, D., & Preece, J. 2004). Thus UCD enhances e-participation in the e-government context.

Audience segmentation is a practice of clustering an audience based on mutually exclusive subsets of individuals that are similar in specific ways to make up hypothetical archetypes of actual users. Audience segmentation has been defined as ``the process of identifying groups of customers who are relatively homogenous in their response to marketing stimuli, so that the market offering can be tailored more closely to meet their needs'' (Brennan, R., Baines, P., & Garneau, P., 2008). The goal is to find new, previously unaddressed target groups of customers to better design communication strategies catering them in an suitable way according with their specific needs to increase their satisfaction and loyalty. The segmentation could be based on demographic issues (i.e. age, gender, region, ethnic); social-economical features (i.e. sector, services access, income); psychographic data (i.e. lifestyle, values, attitudes, interests, activities, opinions), physical characteristics (disabilities, perceptual abilities, motor skills abilities), psychological profiles, and all other measurable criteria that will affect the target.

With the advent of the Digital Society, the idea that people behave differently during the purchase process has been extended beyond the business industry to other fields. In particular, audience segmentation provides key insights to the field of UCD, where achieving and accurate understanding of user's behavior is becoming a complex task (Liu, Y., Osvalder, A., & Karlsson, M., 2010). An adequate user classification will enhance later definition of user profiles, flexible targeting requirements, personalized design, test cases design, and prediction of user navigation patterns and habits, among others UCD oriented activities.

In the above context, the psychographic and psychological factors (emotions and feeling) treatment is sometimes avoided for considering them too difficult and subjective (Panagiotis, Tsianos, Lekkas, Mourlas, & Samaras, 2008). Indeed, obstacles related to the criteria for segmentation itself emerge, including what data to select, how many clusters to produce and how to evaluate the clustering results. In addition, even some proposals deal with with vagueness and uncertainty (Lefait, G., & Kechadi, T., (2010) (Hiziroglu, A., 2013), coping with the treatment of incomplete, contradictory or potentially inconsistent information is still a challenge to address.

Based on E^2P, a novel UCD-oriented strategy for the automatic detection of critical US factors regarding psychological factors towards a particular topic was proposed (González, Chesñevar, & Brena, 2015). The goal is to enhance E^2P by adding to traditional construction process novel tools to support the computational treatment of incomplete, contradictory or potentially inconsistent information, as well as novel mechanisms to discover segmentation issues when dealing with user’s feelings and opinion.

Figure 5. Opinion tree for the query “Windows 8” (computed from Twitter, 2014)

Figure 6. Conflict tree derived from the Opinion tree for the query “Windows 8”

Figure 5 illustrates how the construction of an opinion tree for the query Q= ``Windows 8'' looks like (computed in 2014). As in the abortion example, the original query Q has cardinality 1, and further levels in the opinion tree refer to incrementally augmented queries that may or may not change the prevailing sentiment associated with the root node. Leaves correspond to arguments associated with a query Q which cannot be further expanded. Instead of assuming a probable segmentation criterion when dealing with people emotions, factors determining internal branches of the computed trees showed both the most significant segmentation criteria (expressed in the root of the obtained tree) and the more specific segmentation criteria (such as ``stability'' or ``usability''). This way, novel and non-evident or unexplored segmentation criteria should emerge, showing the real factors that are determining the user's feeling toward a topic without previous conjectures or assumptions.

Besides, the E^2P automatic calculation provides a reasonable resource to re-calculate the same query at different times, thus providing evidence about the evolution of psychographic and psychological factors over time. Figure 6 presents the conflict tree derived from the opinion tree shown in Figure 5.

6. 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 (Cartwright & Atkinson, 2009), 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 (Torroni & Toni, 2011) coined the term *bottom-up argumentation*, as they take a grassroot 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 (Heras et al, 2010), the authors show how the theory of argumentation schemes can provide a valuable help to formalize and structure online 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. (Klein & Iandoli, 2008) 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.

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, (Abbas & Sawamura, 2012) 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 underlying arguments in social networks as done in this paper.

Figure 7: Conflict Resolution (CR) in the context of EGOV

Finally, we argue that the application of the framework presented in this chapter serves as an important novel tool for governments to process and create public value from citizens' opinion, addressing an important problem, such as conflict resolution raised by contradictory opinions in the society, in government decision making processes. We argue that the solution presented here, is a seminal work for a very promising area - Electronic Governance (EGOV) for Conflict Resolution. As shown in Figure 7, the area of conflict resolution presents the problem domain - raising problems related to stakeholders' conflict of interests, social or other type of conflicts, to be solved by EGOV - technology-enabled governance mechanisms, which in turns defines the solution domain. We justify the novelty of the area, since searches in the SCOPUS database with the following keywords: 1) "conflict resolution" and "electronic government"; 2) "conflict resolution" and "electronic governance"; and 3) "conflict resolution" and "digital government", in the articles titles, abstracts, and keywords of the database produced zero results in all three cases. The same searches in Google Scholar produced 579, 143, and 313 results, respectively, compared with the over 2 million results that are obtained when searching separately for "electronic government", "electronic governance" and "conflict resolution", and more than 1.9 million results for "digital government". The figure illustrates two case studies of conflict resolution illustrated in Section 5, example of governance mechanisms available to solve such issues as explained in the Introduction, and a concrete solution - the tools provided by the E^2P framework introduced in sections 3 and 4.

7. Conclusions. 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 (García & Simari, 2004). 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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