# SePoMa: Semantic-Based Data Analysis for Political Marketing

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**Abstract.** Political marketing is a discipline concerned with the study of the right political communication strategies. Precise decision making in political marketing largely depends upon the thorough analysis of vast amounts of data from a variety of sources. Relevant information from mass media, social networks, Web pages, etc., should be gathered and scrutinized in order to provide the insights necessary to properly adjust the political parties' and politicians' messages to society. The main challenges in this context are, first of all, the integration of data from disparate sources, and hence its analysis to extract the relevant information to use in the decision-making process. Big data and Semantic Web technologies provide the means to face these challenges. In this paper, we propose SePoMa, a framework that applies semantic Big data analysis techniques to the political domain to assist in the definition of political marketing strategies for political entities. SePoMa explores the pertinent structured, semi-structured and unstructured data sources and automatically populates the political ontology, which is then examined to generate electorate knowledge. An exemplary use case scenario is described that illustrates the benefits of the framework for the automation of electoral research and the support of political marketing strategies.

**Keywords:** Semantic big data analysis · Political marketing · Ontology Ontology population

## 1 Introduction

More than ever, modern political campaigns rest on strategies formulated based on what is known as political marketing. Political marketing consists on the application of market research techniques and advertising concepts to political communication [1]. It encompasses most of the political process, from the definition of the political product through a rigorous analysis of the citizen's needs, to the development of the political campaign and the management of the political communication [2]. The main aim of political marketing is to assist in tracking and forming public opinion [3] as well as


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persuading the electorate through both traditional media (e.g., radio, TV, etc.) and new digital media (e.g., social networks, apps, etc.). As part of the political marketing process, it becomes essential to collect as much information as possible about prospective voters. Electorate data gathering should be performed both before and during the political campaign to define the electoral strategy [4]. Certainly, the success of the political strategy is closely related to its alignment with the interests and concerns of society [5]. However, dealing with data about thousands, maybe millions, of voters is a very challenging endeavor.

Big data is a novel approach to data analysis mainly characterized by three properties of the data being processed, namely, volume (i.e., size in bytes), velocity (i.e., data growth rate), and variety (i.e., data format and data source heterogeneity), which are known as the 3Vs of Big data [6]. Other Vs or properties typically associated with Big data are value, veracity, volatility, validity and viability [7]. A more formal definition of Big data is provided in Gartner and describes Big data as "*information assets characterized by their high volume, high speed and high variety, which demand innovative and efficient processing solutions for the improvement of knowledge and decision-making in the organizations*" [8]. Given these properties, a number of challenges should be considered when dealing with Big data in data analysis implementations, from the extraction and linking of heterogeneous data coming from diverse sources, to the analysis, organization, modeling and visualization of the obtained knowledge [9, 10].

The technologies associated to the Semantic Web [11] and Linked Data [12] have proved effective for the automatic treatment of information in different contexts [13, 14]. The underlying ontological models, which are based on logical formalisms, enable computer systems to somehow interpret the information that is being managed [15]. They also allow to carry out advanced reasoning and inferencing processes [16]. The scientific community within these research fields have developed tools that make use of semantic technologies to both (i) integrate data from heterogeneous data sources [17, 18], and (ii) allow the analysis of large amounts of data at the knowledge level [19], with different degrees of success. In this paper, we propose SePoMa, a framework that integrates Big data analytics techniques with Semantic Web technologies to assist in the definition of political marketing strategies through the gathering and analysis of electorate data available all over the Internet. To the extent of our knowledge, there are no other works in the literature focused on the exploitation of semantic technologies in the political marketing domain.

The main aim of the framework described in this work is to improve the efficiency of political marketing processes thus obtaining better results, specifically in market research and data analysis. In order to do that, the proposed system incorporates a semantic layer that enables a more advanced data processing and inferences capabilities. With all, data coming from disparate, heterogeneous sources can be seamlessly integrated and processed at the knowledge level, providing more precise insights on the needs, concerns, and viewpoints of the electorate. The benefits of exploiting these insights in the political marketing context are manifold. First, SePoMa offers a broader and more precise knowledge about potential voters through a faster and cheaper mechanism than traditional methods (i.e., surveys and interviews). Second, the collected data can assist in predicting election results. Finally, the proposed approach promotes a new research area that supports the use of these new methodologies for the development of efficient digital political marketing campaigns.

The rest of the paper is organized as follows. In Sect. 2, background information on political marketing and the application of semantic technologies to enhance Big data analysis processes is provided. SePoMa, the framework proposed in this work to facilitate political marketing by leveraging semantically-enabled data analysis tools, is described in Sect. 3. In Sect. 4, an exemplary use case scenario that illustrates the benefits of the framework for the automation of electoral research and the support of political marketing strategies is described. Finally, conclusions and future work are put forward in Sect. 5.

## 2 Related Work

Today, most political parties carry out some kind of market analysis to acquire deep insights about society's main concerns, likes, dislikes, needs and preferences. Also, the reaction of citizens (positive or negative) to government performance, political proposals and news is checked with the aim of defining the right political strategies. The use of such insights with the purpose of improving political communication is referred to as political marketing. In this section, the field of political marketing will be characterized and the impact of Semantic Web technologies in the area of Big data analytics will be discussed.

### 2.1 Political Marketing

Political marketing began in the 1950s when for the first time an US president, Dwight Eisenhower, hired an advertising agency to take charge of his television campaign. This meant the incorporation of market research techniques and advertising to political communication. In [5] political marketing is defined as "*the discipline oriented to the creation and development of political concepts related to specific parties or candidates to satisfy certain groups of electors in exchange for their votes*". According to these same authors, the key principle of political marketing is the application of marketing concepts to the overall behavior of the political institution. This leads to (i) the design of political products using marketing intelligence becoming voter-centric, (ii) the definition of behaviors for politicians and their parties, (iii) the development of open offers for the electorate, and (iv) the measurement of the degree of coverage of the needs of the electorate that reach those offers and products.

There are three fundamental aspects linked to political marketing [20]: (i) the political product, (ii) identification and segmentation of the voter market, and (iii) marketing intelligence applied to politics. The political product refers to the ideas to be transmitted by politicians and parties, which must be defined from the identification of the electorate needs. On the other hand, electorate segmentation consists of dividing the heterogeneous electoral mass into smaller sections that have something in common with the objective of detecting large enough groups to which the political product can be especially attractive. For this, different techniques can be used such as geographic (i.e., the place where people live according to regions and zones within those regions), behavioral (i.e., based on the actions of the individual), demographic (i.e., age, type of family, social class, income, etc.) or psychographic (i.e., characteristics of lifestyle, common values, beliefs, attitudes, activities, interests and opinions). Finally, marketing intelligence enables the understanding of what the political market, that is, the electorate, wants from political elites, that is, political parties and candidates, using quantitative and qualitative research techniques. The ultimate goal of marketing intelligence is to place the political product in an ideological niche that is unapproachable by competitors because of its competitive advantage, which is capable of attracting the sufficient number of votes to achieve the desired electoral goal.

In response to these principles of political marketing, it is increasingly common in modern political campaigns for parties to resort to the analysis of large data sets and its power to predict the future, enhancing their competitive advantage, and attributing much of their success to the speed and reliability of processing information transforming it into electoral knowledge. Nowadays, the Internet, and its hundreds of new collaborative and informative technologies, where the user is creator of information and opinion leader, generates a collective intelligence environment, but it is difficult to obtain, classify, sort and store in specific domains to be used for electoral purposes [3]. The technologies associated with the Semantic Web have proven useful in the integration of data from heterogeneous sources [17, 18] and in the analysis of data at the knowledge level [19]. In the last few years, ontologies specifically, and semantic technologies in general, have been used in the political domain for various purposes, but mainly focused on decision making [21–23]. In [24], the authors propose a methodology for building a political ontology by extracting knowledge from various data sources. The goal is to provide decision makers with an intelligent decision process in this domain. Finally, in [25] one of the most outstanding challenges in political marketing, that is, the administration and extraction of useful knowledge from the content publish in social sites, is partially overcome by means of an ontology-based approach and the semantic analysis of the data.

### 2.2 Semantic Technologies in (Big) Data Analysis

For many years, companies have exploited the data registered in their transactional systems concerned with their everyday operations in order to obtain useful information and assist in the decision-making process. To this end, different data analysis techniques and business intelligence strategies have been applied. Data analysis includes the processes associated to data inspection, cleansing, transformation and modelling, with the objective of producing useful information, leading to findings, and supporting decision making [26]. The technological architecture of most data analysis solutions is comprised by three main components [27]: (i) tools for data extraction, transformation and loading (ETL), (ii) a repository to store the integrated data, namely, data warehouse, and (iii) data processing and visualization systems, including report generators, multi-dimensional analysis techniques (OLAP), and statistics-, symbolic- or artificial intelligence-based data mining methods. In recent years, the increase in the volume of data, along with variety in data and the velocity at which data is being produced, has led to the conception of novel processing mechanisms capable of dealing with such huge amount of data, namely, Big data [6]. In general terms, the Big data and data analysis processes include three main stages, namely, data pre-processing, data processing, and data visualization.

The main difficulties associated with Big data management are linked to its collection and storage, search, sharing, analysis and visualization [10]. The Semantic Web provides the means to overcome some of these challenges. Certainly, the formal underpinnings of Semantic Web technologies enable the automated processing of data through sophisticated inference and reasoning techniques. RDF (Resource Description Framework) is a standard model for data interchange on the Web and is based on graphs, allowing the representation of data in the form of triples subject-predicate-object [28]. RDF triples can be used to create datasets and to establish explicit relationships among data; this collection of interrelated datasets on the Web is referred to as Linked Data [12]. One of the main aims of Linked (Open) Data is to add a semantic layer over the data, making it understandable by machines so that they can perform some data analysis operations on behalf of human users [29]. Thus, the Semantic Web can assist in the discovery, integration, representation and management of knowledge [30]. In particular, semantic technologies have been successfully applied in a number of scenarios for the integration of heterogeneous data [31], data analysis at the knowledge level [30], and visualization of Linked Data [32].

In the last few years, a large number of published research papers have explored the benefits in using semantic technologies in data analysis and Big data [19, 25, 31, 33–36]. The impact of semantics in this field covers the whole process, from pre-processing (data acquisition and organization) to visualization through data processing and analysis. Ontology models can be used to harmonize heterogeneous data from structured, semi-structured and unstructured sources, thus allowing its integrated storage in ontology repositories [31]. The formal grounding of the Semantic Web enables reasoning processes useful to infer new knowledge not explicitly stated in the source data [34]. Finally, many tools have been proposed that provide retrieval and visualization features for Linked Data and Big Linked Data [35, 36].

## 3 Knowledge Management for Political Marketing

Political marketing requires the use of market research techniques that perform a systematic and objective extraction and use of information in order to improve decision-making processes related to the identification of problems and opportunities, and the generation of their corresponding responses. In a political context, this can help to find unmet needs or demands within a segment, niche or sector of the population. In this section, we present SePoMa, a semantic-based political marketing framework that first generates a politics-related knowledge base by gathering information from multiple, heterogeneous sources, and then, analyses such knowledge base in order to understand the electoral market and assist political strategists in the definition of the communication objectives to improve the performance of the political campaign through the candidate-citizen communication. For this, qualitative and quantitative research on the target electorate is essential, applying geographic and time limits.

### 3.1 Proposed Framework

The functional architecture of the SePoMa framework is shown in Fig. 1. It is composed of four main elements: (i) an ontology population component, responsible for gathering knowledge from heterogeneous sources, (ii) a knowledge base built on top of a political ontology, where the gathered knowledge is stored, (iii) a semantic data analysis tool, which explores the knowledge base collecting relevant information items, and (iv) the electorate knowledge component, which include the knowledge items to be visualized by external users for assisting in the decision-making process.

In a nutshell, the SePoMa framework works as follows. First, relevant data sources are identified. These data sources could be either structured, such as databases with relevant information about the affiliates of political parties, semi-structured, such as XML or JSON files with citizen participation at different events[1], or unstructured, such as the content published by eligible voters in Web 2.0 sites. Different ontology population strategies are then employed to deal with those disparate and heterogenous sources, ant to create ontology instances in the knowledge base. The knowledge repository is based on a political ontology that covers the main concepts, insights and relationships within the political domain to respond to the questions and needs of political marketing. Once the knowledge base has been populated, semantic data analysis techniques are used to extract meaningful knowledge related with (i) the design of political products, (ii) the definition of behaviors for politicians and their parties, (iii) the development of open offers for the electorate, and (iv) the measurement of the degree of coverage of the needs of the electorate that reach those offers and products, as required in a political marketing scenario. All this knowledge is then exposed through the electorate knowledge component, which includes the tools to assist in the proper visualization of the analyzed data by end users.

Next, the components that comprise the SePoMa framework are described in detail.

### 3.2 Political Ontology

In the last few year, a large number of ontologies in the political domain have been developed [37–40]. They all focus on "government" and "government services", and none of these ontologies include some of the most relevant concepts required in a political marketing context for the definition of the correct political communication strategies. Under these circumstances, the political ontology to be used in the SePoMa framework was built from scratch, but has been linked, when possible, to well-known ontology models such as FOAF[2], the Organization Ontology[3] and DBpedia[4], among others. For the design of the ontology, three fundamental political marketing-related research questions were considered:

1. What opinions do citizens have about the candidates and the political parties?

[1] https://catalog.data.gov/dataset/citizen-participation.

[2] http://www.foaf-project.org/.

[3] https://www.w3.org/TR/vocab-org/.

[4] https://wiki.dbpedia.org/services-resources/ontology.

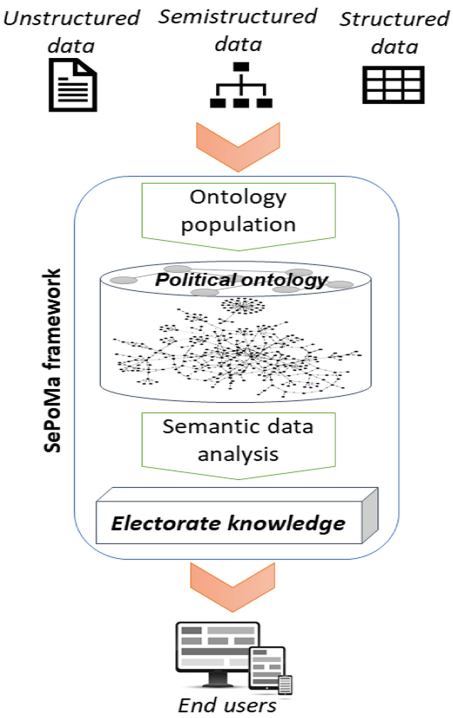


**Fig. 1.** SePoMa functional architecture

2. How are the candidates' and political parties' proposals in the core elements of political issues (i.e., health, education, economy, law and order, etc.) received by society?
3. How are candidates and political parties positioned in comparison to their opponents?

The ontology, which has been defined in OWL 2[5] using Protégé[6], contains five main concepts (see Fig. 2), namely, candidates, political parties, political proposals, electorate and opinion. These elements enable SePoMa to answer to the aforementioned questions and can be defined as follows:

- `Candidate`: person affiliated to a political party who has made known his or her intention to seek, or campaign for, local or state office in a general, primary or special election.
- `PoliticalParty`: organized group of people with common values and goals, who try to get their candidates elected to office.

[5] https://www.w3.org/TR/owl2-overview/.

[6] https://protege.stanford.edu/.

- `Politics`: proposals suggested by candidates or political parties as to how the country or jurisdiction should be governed.
- `EligibleVoter`: person who has the right to vote at an election.
- `Opinion`: the expression of a belief or judgment with respect to political proposals or news about the main political themes (i.e., health, education, economy, etc.).

### 3.3 Ontology Population

Ontology instantiation has to do with the extraction and classification of instances of the concepts and relations that have been defined in the ontology. Instantiating ontologies with new knowledge is a relevant step towards the provision of valuable ontology-based knowledge services. However, performing such task manually is time-consuming and error-prone. As a result, research has shifted attention to automating this process, introducing ontology population, which refers to a set of methodologies for automatically identifying and adding new instances of concepts from an external source into an ontology [41]. Ontology population does not affect the concept hierarchies and the relations in the ontology, leaving the structure of the ontology unmodified. What is affected are the individuals (a.k.a. concept instances) and the relationships between individuals in the domain.

The political ontology described in the previous section constitutes the backbone of the knowledge repository in the SePoMa framework. In order to populate the knowledge base with the relevant instances from the identified data sources, an ontology population component has been conceived. This component makes use of different strategies in order to cope with the challenges related to each of the different data source models considered, namely, structured, semi-structured and unstructured data sources. A rule-based approach as suggested in [42] has been used to deal with structured content. This module consists of a set of rules describing the transformation steps to gather the data from known relational databases and generate the ontology instances. Similarly, the ontology population from semi-structured data module follows the guidelines described in [43]. This module is comprised of a document parser, which transforms the input data into a common representation format in JSON, and a JSON2RDF algorithm, which produces the ontology instances by making use of an 'affinity' function that identifies the ontology classes each instance belongs to. As for unstructured content, a sentiment analysis (a.k.a., opinion mining) approach as shown in [44] has been considered. It involves the calculation of the polarity (i.e., positive or negative orientation) of the different features that can be found in free text documents (such as news or users' posts in social sites).

Finally, Linked Data sources have been also considered as a valuable input data source for the SePoMa knowledge base. For this purpose, a user-friendly graphical user interface application called PROPheT[7] is used. PROPheT enables instance extraction and ontology population from Linked Data by (i) gathering instances through searches via SPARQL endpoints, (ii) enriching those instances with data properties, and

[7] http://mklab.iti.gr/project/prophet-ontology-populator.

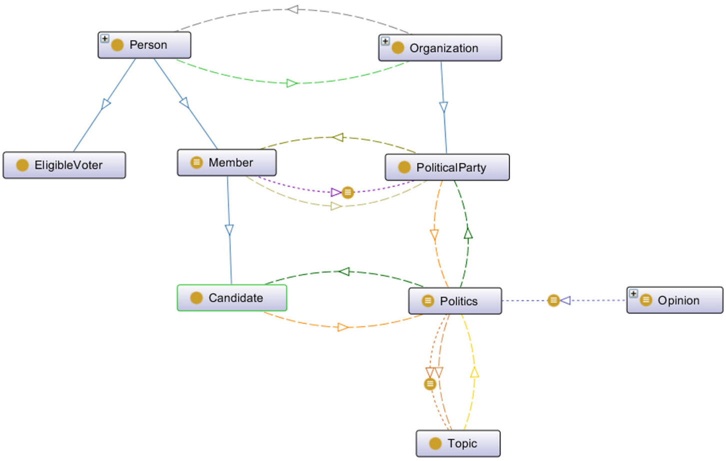


**Fig. 2.** Excerpt of the political ontology

(iii) mapping it all to a given ontology model. With all, the proposed ontology population component assists in the quick, easy and automatic collection and classification of large volumes of information.

### 3.4 Semantic Data Analysis

Ontologies facilitate the management of information at the knowledge level and enable an integrated access to heterogeneous sources, being able to use various inference and reasoning techniques to analyze the data [19]. However, it has been demonstrated that the analysis of large volumes of data has implications for knowledge management [45]. In order to handle such a huge amount of data, different solutions have been proposed [19, 33, 46–49]. One possibility is the use of the concepts and methods of Formal Concept Analysis, which is a method where data are structured into units that represent formal abstractions of concepts of human thought, allowing comprehensive interpretation, and facilitating the representation of knowledge and the management of information [19, 33]. Another relevant approach in this context is the generation of a multidimensional ontology layer to consolidate the analysis at different levels on the repository, so as to add more meaning to the data, eliminate redundancies and irrelevant information, and to obtain an enhanced analysis [19].

OLAP (Online analytical processing) systems can also benefit from the use of ontologies [46]. The ontological model, which provides an unambiguous definition of the domain terms associated to the specific needs of OLAP, strengthens the correlation and enrichment of the data automatically with grouping algorithms. It also provides the means to perform tasks of comparative analysis of highly heterogeneous data originating from different sources, platforms and technologies. In [47], the authors suggest the use of rules expressed in SWRL (Semantic Web Rule Language) along with the intrinsic inference mechanisms of ontologies to analyze knowledge bases thus producing new relevant knowledge.

The potential shortcomings that can arise from the application of ontology-based big data management have been explored in [49]. The complexity of the reasoning process and the related performance issues can be addressed by considering ontology languages that trade expressivity for reduced reasoning complexity. Yet, the benefits are massive. The integration of new data sources is facilitated, and usability is boosted. Both reusability of data and maintainability of applications can be also improved with the use of semantics. The visualization of knowledge is impacted too, since it is possible to represent information in different forms thus enhancing end users understanding of the insights derived from the knowledge base.

### 3.5 Electorate Knowledge

The outcome of the semantic data analysis component is specific pieces of knowledge that can respond to the needs of political marketing. That knowledge, which is related to the research questions set out in Sect. 3.2 to support decision making in this context, is represented in the SePoMa framework as the electorate knowledge component. That is, once the SePoMa framework has collected the data from the different sources, organized it, and effectively analyzed it, it produces the relevant electorate knowledge which is to be shown to the political marketing strategists.

The next logical step is to provide end users the means to explore and visualize the relevant knowledge. Vital requirements at this stage are scalability, functionality and response time [35]. However, it is necessary to take into consideration some challenges that might arise due to the large size and dynamic nature of the data, coupled with the problems related to performance. One of the most interesting proposals to face these issues is the so called 'Linked Data Visualization Model' [32], which is an adaptation of the 'Data State Reference Model' (DSRM) [50] conceived to visualize RDF and Linked Data. In addition, it extends DSRM with three reusable software components, namely, analyzers, which that generate the RDF representation of data sources, transformers, which produce an appropriate RDF structure according to the visualization technique to be used, and visualizers, which create the visualization for end users.

## 4 Use Case Scenario

In order to devise the potential benefits of the application of the SePoMa framework in a real environment, in this section an illustrative use case scenario is presented. The basic idea behind this sample scenario is to show the typical process flow in political marketing and describe the usual actors involved. SePoMa would be placed in the spotlight of the scenario to provide the electorate knowledge that supports decision-making processes for the definition of communication strategies in political marketing (see Fig. 3).

The exemplary scenario is depicted in Fig. 3. Candidates or political parties (1) define sensible political, economic and social proposals (2) which are then transmitted through mass media (3) to the citizens (4). The conveyed messages cause an

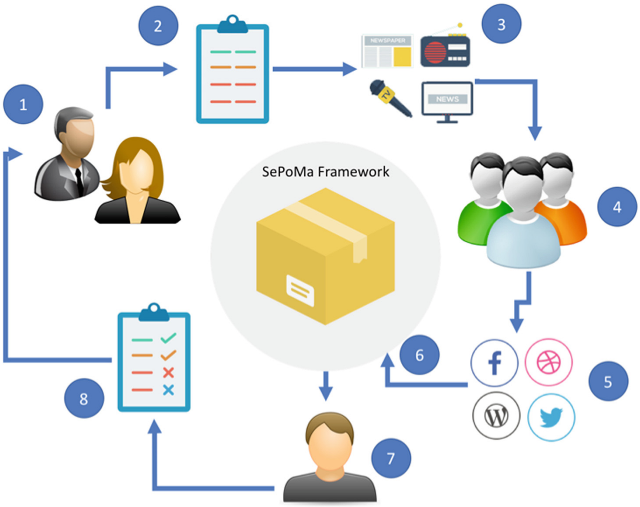


**Fig. 3.** The SePoMa framework in its context

impact on citizens, who share their feelings by posting text comments to different websites (5). Then, SePoMa collects the data from the different sources, organize it, and effectively analyze it, producing the relevant electorate knowledge (6). Political marketing strategists make use of the proper visualization tools to get access to the required knowledge (7) and take advantage of it to adjust the policy proposals (8). At that moment, the process starts over again, but this time the candidates' and political parties' communication strategy is better aligned to the changing needs of citizens.

During the recent Mexico's 2018 Election, social networks were the main means of interaction for the average citizen, where they not only participated critically, but used it as a form of communication and graphic reaction (e.g., Internet Meme[8]) to the different events, statements or incidents of the candidates' public activities. Quantitative analyses were performed[9], which shown that the winning candidate (Andrés Manuel López Obrador) had a greater impact on social media than his opponents. SePoMa could help enhance the insights derived from these analyses and assist in defining the best political marketing strategies prior and during the elections process. With SePoMa it would be possible to integrate data coming from heterogenous sources, analyze such data at the knowledge level, and show the most interesting elements to the political strategist.

8 http://www.scielo.org.mx/scielo.php?pid=S0187-57952014000200005&script=sci_arttext [Accessed: 17-Jul-2018].

9 http://www.eluniversal.com.mx/elecciones-2018/amlo-el-candidato-que-mas-crece-en-redes-sociales [Accessed: 17-Jul-2018].

## 5 Conclusions and Future Work

In order to make decisions in political marketing, it is very important to know the sentiment of the electorate towards candidates, political parties, and their proposals, which can be referred to as 'electorate knowledge'. With this purpose, in this paper we propose a framework with capabilities for extracting data from various sources, organize the gathered data, and create semantic relationships between the data items. The resulting ontology-based knowledge repository can enable a more sophisticated and precise analysis which can lead to a better feedback to improve the political message and the communication strategy.

As future work, we plan to test the solution in a real environment. Different tests should be carried out to check the efficiency and effectiveness of each distinct component of the framework. On the other hand, the ontology model used in the framework is in continuous change so that it takes into account all the relevant concepts to better support the decision-making process. We will study the possibility of integrating an ontology evolution approach to automate the update of the ontology scheme. With the aim of defining a framework as flexible as possible, making it even suitable for other domains beyond political marketing, a plugin set up will be considered. Once in place, anyone will be able to use the framework with their own built components for ontology population or semantic data analysis.

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