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Dynamic profiles using sentiment analysis and twitter data for voting advice applications

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ABSTRACT

Nowadays, political campaigns combine traditional media channels with social media platforms, opening new and promising possibilities for parties and candidates looking for better political strategies and visibility. Voting advice applications (VAAs) recommend parties and candidates that are close to a citizen's political preferences and require the constrution of candidate and party profiles. Profile generation is an essential task in the development of VAAs and requires two steps: an unbiased design of political questionnaires and the collection of all candidates' answers. This paper presents an extension of a VAA, implemented in within the project *Participa Inteligente* (PI), a social-network platform designed for the 2017 Ecuadorian national elections. This work concentrates on the implementation of dynamic candidate profiling using Twitter data and sentiment analysis as an additional element to the static profile generation of VAAs. The implementation of a dynamic element for VAAs could help mitigate the effect of biased recommendations given during the construction of candidate and party profiles. At the end of this work, the dynamic profile is compared with the classic static elements developed within the PI project. The results show the level of similarities and differences between each of the elements in profile generation. This work provides an ideal basis for future research in the area of VAAs and their interfaces. Additionally, it opens up a broader spectrum of applications for policymakers including decision-making and collaborative working environments toward e-empowerment.

1. Introduction

The use of recommender systems (RSs) in e-democracy is a research area intended to reduce information overload on e-government services and enhance interactions among public administrations, citizens, and the private sector. Two types of RSs were identified: The first one corresponds to voting advice applications (VAAs), which are online tools that match the preferences of citizens with respect to political parties or candidates. These applications are mainly used in electoral campaigns. In (Ladner, Fivaz, & Pianzola, 2010), the authors conclude the increasing popularity of VAAs. The second type of RS in e-government is a social voting advice application (SVAA), as proposed in (Katakis et al., 2014). The authors defined an SVAA as an extension of VAAs that provides community-based recommendations, comparisons of users' political opinions, and a channel for user communication.

The application and development of VAAs fail to keep the candidate's profiles up to date. This profiles are used to provide, either a recommendation or an authentic ideology representation of a candidate, matching different social topics. In general, VAAs update the candidateâ€™s profiles manually, either by candidates themselves (answers submitted to VAA developers before the elections) or by experts who determined the ideology of all candidates in different social categories.

From this perspective, it is possible to include a biased profile given that candidate's opinions could be authentic or based on a political strategy. This problem produces biased and static predictions that could be valid for a limited amount of time on VAAs that follow this method.

In any case, the political profiles do not evolve according to the speech of a candidate during the campaign. Candidates could change strategies during the campaigns to convince different groups of voters and in most cases, the new profiles (political speech) are not updated in the VAAs.

One of the objectives of this work is to propose a profile generator model based on dynamic elements using Twitter social media as a data source to collect political speech. It allows the VAAs to update automatically and reduce the candidate profile bias. Additionally, the implementation in a case study of the 2017 Ecuadorian national elections is used to evaluate the model. The theoretical approach was proposed

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for the first time in the work of Terán and Mancera (2017b). It extends classic VAA design methods (static), in which candidates' profiles are mainly generated on the basis of a standardized questionnaire that includes a number of questions on political issues. Once the questionnaires are developed, data collection can be carried out by retrieving either the answers of candidates themselves or the support of experts who answer the questionnaires as if they were the candidates.

As an example of a classic VAA that uses the answers of candidates is *smartvote*, which is used for communal, cantonal, and national elections in Switzerland. It is based on profile comparisons between candidates and voters (*smartvote*, 2003). *smartvote* generates the candidates' profiles from a set of 30 to 75 questions on 11 political issues (e.g., welfare; family and health; migration and integration; economy and work).

Preference Matcher,[1] another approach to generate candidates' profiles, is based on the opinions of experts who answer the questionnaires as if they were the candidates themselves using a Delphi iterative expert survey until it reaches consensus on the profiles of all candidates.

In (Terán & Drobnjak, 2013), the author concludes that one of the limitations of VAAs is that these applications are mainly used during voting or elections and are no longer used when these processes end. With the inclusion of so-called dynamic profiles and in allowing users to become content generators (Terán, 2014), a dynamic VAA, implemented in the project *Participa Inteligente* (PI), intends to improve the participation of users and provide more accurate recommendations of candidates.

The academic community fosters an important discussion regarding the potential of VAAs to enhance citizens' decision-making. Nevertheless, problems such as biased answers of candidates and experts need to be tackled for further leeway in the conversation. This work intends to provide one additional mechanism to help mitigate this problem. At the same time, it opens up the possibility of including citizens' perceptions about candidates as an additional element in the construction of profiles using Twitter as a data source.

An application of the theoretical framework (see Section 4), originally proposed by Terán and Mancera (2017b), and adapted on real case study for the 2017 Ecuadorian national elections (see Section 5) is presented in this paper. Additionally, a discussion is proposed on how the use of VAAs can be extended not only as a tool to provide recommendations about candidates or parties but also as a mechanism for discussion between citizens and its impact on policymakers toward *e-empowerment*.

The paper is structured as follows. Section 2 presents a state-of-the-art design of static VAAs together with theoretical notions and background. Section 3 details the research approach used in this work and the steps and research methods used. Section 4 describes the methodology used to generate dynamic candidate profiles in VAAs and the data sets used in this work. Section 5 focuses on the implementation of a dynamic VAA. Section 6 reviews the developed evaluations of static and dynamic elements in VAAs. This section also presents a user-based evaluation to show the perception of users on the received recommendations. Section 7 introduces a discussion of advantages, disadvantages, and risks. Finally, Section 8 presents some concluding remarks, scientific contributions, implications, limitations, and recommendations for future work.

2. State-of-the-art

In recent years, political and social scientists interested in the study of VAAs as a major feature of election campaigns prior to national or regional elections in different countries have led the research on VAAs (Cedroni & Garzia, 2010; Garzia & Marschall, 2014b). The European Consortium for Political Research (ECPR)[2] introduced a specialized research community on VAAs as a subfield of political-science research resulting in several research projects and publications. The ECPR Research Network[3]on VAAs presented The Lausanne Declaration on Voting Advice Applications (Garzia & Marschall, 2014a), whose aim is "to serve as a starting point for the debate on the professional and ethical aspects of making VAAs. It owes its name from a workshop held in Lausanne in May 2013 at which all contributors of this work took part and where such issues were debated."

To better understand the impact that VAAs have in the context of Europe, Table 1 shows a list of countries who most use VAAs. The level of participation shown in countries such as the Netherlands, Finland, and Germany shows that VAAs have already become institutionalized, given that a significant proportion of the electorate uses these applications.

Even though the study of VAAs are seen more from a political and social point of view, the development and implementation of such applications is gaining the attention of technical-oriented networks, including VAAs, within the scope of their research fields. Communities related to RSs, data mining, social computing, and e-government, among others, are also attracting researchers with contributions related to VAA developments (Agathokleous & Tsapatsoulis, 2013; Agathokleous & Tsapatsoulis, 2016; Agathokleous, Tsapatsoulis, & Katakis, 2013; Andreadis, 2013; Etter, Herzen, Grossglauser, & Thiran, 2014; Galbrun & Miettinen, 2016; Katakis, Tsapatsoulis, Triga, Tziouvas, & Mendez, 2012; Tsapatsoulis, Agathokleous, Djouvas, & Mendez, 2015; Tzitzikas & Dimitrakis, 2016).

2.1. VAAs design

VAAs' designs are based on matching user profiles with parties or candidates based on a set of policy statements defined for a political sphere and society that are influenced by the political structure of the country for which the VAA is developed. The basis for this matching is a multiple-choice questionnaire, normally comprising 30 to 70 questions. All VAAs consist of three broad components. The main page attracts users and attempts to gain their interest.

Several differences exist among VAA designs, as well as the goals of each project. Some applications are developed by political education agencies, media corporations, research-oriented institutions, nonprofit organizations, and interest groups. The question-selection process is generally not standardized and varies between the different VAAs. Often, a VAA can also include weight values for each answer.

Designing and constructing candidate profiles are complex and essential tasks that are needed to provide recommendations to citizens. It is important to take into consideration that, in most cases, the candidates are unwilling to answer the questions proposed by the VAA developers. In practice, two main methods are used to construct candidate profiles: using the answers provided by parties and/or candidates themselves or using the answers provided by experts (e.g., academics, journalists) about parties and/or candidates' political positions.

Moreover, the matching process is not the same for every VAA; different types of algorithms are applied, taking into account that answers are also compared and weighted differently. A VAA design can be separated into four areas, as shown in Fig. 1.

2.1.1. Questionnaire

In (Garzia & Marschall, 2014c) describe the state-of-the-art on VAA research up to 2014. They show that in early studies, VAA research concentrated on the characteristics of users (Boogers & Voerman, 2003; De Rosa, 2010; Dziewulska, 2010; Edwards, 1998; Trechsel, 2007; Wall, Sudulich, Costello, & Leon, 2009). Based on the impact and growing

[1] Preference Matcher: http://www.preferencematcher.org

[2] ECPR: https://ecpr.eu

[3] VAA Research Network: http://vaa-research.net/

Table 1
Most used VAAs in Europe. Adapted from (Marschall, 2014).

VAA and country	Highest score (HS)	Year of HS	Year of first use	Size of electorate (year of HS)	Voter turnout (year of HS)	% of HS/voter turnout
BssolaEleitoral (Portugal)	175,000	2009	2009	9,519,921	5,681,258	3.1
Cabina Elettorale (Italy)	2916	2009	2009	50,276,247	32,748,675	0.0
Choose4Greece (Greece)	92,007	2012	2012	9,949,401	6,476,751	1.4
Do de Stemtest! (Belgium)	840,000	2004	2002	4,568,250	4,284,656	19.6
Help-MeVote (Greece)	480,000	2012	2012	9,949,401	6,476,751	7.4
Help-MeVote (Iceland)	30,000	2013	2013	237,957	193,792	15.5
Kieskompas (Netherlands)	1,500,000	2010	2006	12,524,152	9,442,977	15.9
KohoVolit CZ (Czech Republic)	150,000	2010	2006	8,415,892	5,263,822	2.8
KohoVolit SK (Slovakia)	60,000	2012	2006	4,392,451	2,596,443	2.3
Mano Balsas (Lithuania)	100,000	2008	2008	2,696,090	1,309,965	7.6
smartvote (Switzerland)	437,000	2011	2003	5,124,034	2,485,403	17.6
smartvote (Luxemburg)	15,100	2009	2009	223,876	203,535	7.4
StemWijzer (Netherlands)	4,900,000	2012	1994	12,689,810	9,462,223	51.8
Vaalikone (Finland)	1,000,000	2007	1996	4,083,549	2,772,799	36.1
Valijakompass (Estonia)	111,535	2011	2011	913,346	580,264	19.2
Vote Match UK (UK)	1,200,000	2010	2008	45,597,461	29,691,380	4.0
Wahlkabine (Austria)	850,000	2008	2002	6,333,109	4,990,952	17.0
Wahl-O-Mat (Germany)	13,300,000	2013	2002	61,946,489	43,726,856	30.2
Who should you vote for? (UK)	900,000	2005	2005	44,245,939	27,148,510	3.3

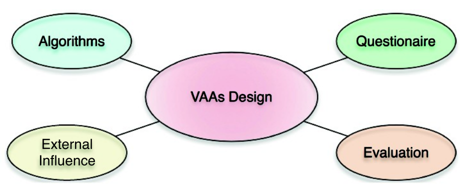


Fig. 1. VAA design elements.

number of users of VAAs, higher levels of transparency were required for the development of questionnaires and policy statements to be able to establish party positions on high-dimensional political maps (Nuytemans, Walgrave, & Deschouwer, 2010; Walgrave, Nuytemans, & Pepermans, 2009). VAA researchers are addressing this element as a key component for the design of VAAs. Large efforts are being made to determine how questions should be chosen, as well as topic weighting and configuration to avoid biased results and influence in the advice provided to users (Gemenis & Ham, 2014; Wagner & Ruusuvirta, 2009; Walgrave, Nuytemans, & Pepernams, 2008).

2.1.2. Algorithms

It is crucial to consider the selection of a method that could affect user recommendations when matching the profiles of parties/candidates to users (Louwerse & Otjes, 2012; Louwerse & Rosema, 2014). The analysis of algorithms, which are used to compare and match candidates with voters, plays an important role in the design of a VAA solution. Some methods used in practice include Euclidean distance, city block, fuzzy clustering, and collaborative filtering, among others (Katakis, Tsapatsoulis, Mendez, Triga, & Djouvas, 2014a; Terán & Meier, 2010; Wall et al., 2009).

2.1.3. External influence

External influence refers to the influence that VAAs have or could have on the political system. The typical user groups and voter groups are analyzed and compared to standard voters and nonvoters. Possible influences from candidates should be tackled and minimized. As an example, a candidate with access to users' data profiles can adapts his/her answers to gain an advantage in the matching process (Fivaz & Felder, 2009; Schwarz, Schädel, & Ladner, 2009; Wall et al., 2009). Additionally, evidence shows that VAA users declared that their voting intentions were influenced by the recommendations provided by different platforms (Aarts & Van der Kolk, 2007; Mykkänen & Moring, 2006; Walgrave, Van Aelst, & Nuytemans, 2008; De Rosa, 2010; Ladner, Felder, & Fivaz, 2010; Dumont & Kies, 2012; 135 Ladner, Fivaz, & Pianzola, 2012; Pianzola, Trechsel, Schwerdt, Vassil, & Alvarez, 2012).

In (Garzia & Marschall, 2014c), the authors mention three types of effects that VAAs can have on users: individuals' information-seeking behavior, cognitive effects, and vote choice, both quantitatively (turnout) and qualitatively (vote intention). Furthermore, research regarding the impact of VAAs shows a correlation between the use of VAAs and electoral participation (Dinas, Trechsel, & Vassil, 2014; Fivaz & Nadig, 2010; Hirzalla, Van Zoonen, & de Ridder, 2010; Ladner & Pianzola, 2010; Marschall & Schultze, 2012; Ruusuvirta & Rosema, 2009).

2.1.4. Evaluation

In addition to considering the implementation and mathematical aspects of VAAs, some researchers attempted to evaluate the quality of advice given by VAAs. One important challenge that VAAs face is the lack of standardization. How can a VAA recommendation be judged as good or bad? This research field seeks to determine whether VAAs are providing neutral and reliable advice without giving an advantage to a party or a specific part of the political system (Wagner & Ruusuvirta, 2009).

In the domain of recommendation systems, evaluation is a subject that requires significant attention and needs to take into account the complexity involved in measuring the impact that the development of recommendation mechanisms can have within different projects and web platforms, which, in many cases, recommend a list of products or numerical predictions of the projected costs of such items.

However, the academic community related to recommendation systems widely accepts that the calculation of precise predictions are crucial but insufficient (McNee, Riedl, & Konstan, 2006). In many cases, users may be more interested in discovering new articles rather than knowing how accurate the system is in predicting their tastes, as well as being able to quickly explore various articles, preserving their privacy, having the ability to generate quick responses from the system and many other properties linked to the recommendation process.

It is essential to identify this set of properties because it can influence the correct implementation of a recommendation system in a specific application. For the evaluation of recommendation systems, there are mainly three types of experiments: offline, user studies, and online experiments, which are detailed below.

2.1.4.1. Offline experiments. Offline experiments are carried out based on information on the behaviors and preferences of pre-established users in order to simulate and establish evaluation parameters for various types of recommendation systems without having to interact with existing users. However, this type of mechanism is limited to measuring the prediction capacity of various algorithms. The main assumption is that the behaviors of the users prior to the implementation of the recommendation system is maintained. For this reason, it is not possible to measure the influence of the recommendation system implemented on user behavior.

2.1.4.2. User Studies. The evaluation of recommendation systems requires not only measuring the prediction capacity of the system but also, in many cases, including the interactions of users with the system. When considering the difficulty of reliably simulating interactions with the system, offline tests are difficult to perform. For this type of evaluation, the user's actual interactions with the system must be collected. Even if it is possible to perform tests offline, interactions with users can provide additional information about the performance of the system. McNee et al. (2006) suggests broadening the scope of the evaluation of recommendation systems and including additional metrics such as retention, user consumption, and system use in the user experience. This method maintains a stronger focus on the â€œHuman-Recommender Interactionâ€ when taking these additional components into account. An adequate evaluation of the user experience requires the preparation of laboratory experiments or random tests carried out on the implemented system, such as type A/B tests.

2.1.4.3. Online experiments. An evaluation process using real scenarios can measure the effect of implementing a recommendation system, which depends on factors such as the user's reason for using the platform, the user's needs, the user's personality, the user's familiarity, the user's trust in the system, the interface, and visualization (i.e., ways in which the recommendations are presented to the user). Online assessments allow for the measurement of objectives for which the recommendation system was implemented. This method allows the properties, advantages, and disadvantages to be understood.

Most VAA projects can be classified as non-personalized RSs; more specifically, they can be considered as case-based RSs with navigation interfaces (i.e., My Product Advisor[4]). In (Terán & Drobnjak, 2013), the authors conclude that one of the main limitations of VAAs is that these applications are mainly used during voting or elections and are no longer used afterward. For further development of VAAs, additional levels of participation to engage users and politicians need to be taken into consideration. One of the most ambitious goals of VAA 2.0 is that the platform could also include e-voting and e-election capabilities, but this is out of the scope of this work.

2.2. Comparison of VAAs

The introduction of e-participation has opened additional channels to citizens, giving them the possibility to take part in the process of shaping the future of their society directly through the Internet. Collaborative working environments, VAAs, social networks, and virtual communities have become a hot topic in today's society. Such technologies could also improve democratic processes, increase citizens' interests in political issues, enhance participation, and renew civic engagement.

In (Terán & Drobnjak, 2013), authors proposed an evaluation framework for e-participation projects that includes three components: Web evolution, media richness, and communication channels. This framework is used to evaluate 21 VAAs and uses the following five layers that can be analyzed separately: e-informing, e-consulting, e-discussion, e-participation, and e-empowerment. The evaluation presented in this work shows that only five out of 21 VAAs reached at least the level of e-discussion. Fig. 2 summarizes the evaluation of participation levels for all VAAs.

The results presented show the limited development of VAAs in terms of e-participation. The creation of political communities and social networks among citizens could allow for interaction and participation through social media, potentially crossing geographical and political boundaries. Contacting people with similar political profiles, building exchange platforms, and stimulating participation will enrich an information- and knowledge-based society in the future. In the classical VAA, neither the candidates nor the voters can generate content (i.e., questions, answers, comments), but in the VAA 2.0 proposed by PI, both candidates and voters can create miscellaneous types of content. With the inclusion of dynamic profiles and by allowing users to become content generators (Terán & Kaskina, 2016), the RS approach described in this work intends to improve the profile generation of candidates who, in most cases, do not respond to the questionnaires proposed by VAA developers. In these cases, their profiles need to be constructed mainly based on expert opinions.

3. Research approach

This project uses Hevner, March, Park, and Ram (2004) guidelines for design science in IS research. This consists of seven guidelines to assist researchers, reviewers, editors, and readers to understand the requirements for effective design-science research. Design science is an information-technology research methodology based on problem-solving that offers specific guidelines for evaluation and iteration within research projects. It focuses on the development and performance of artifacts with the explicit intention of improving the functional performance of the artifact. Design-science research is typically applied to categories of artifacts including algorithms, human/computer interfaces, and design methodologies, among others. Given that the practical outcome of this project is to develop a Web application, the design-science approach gives the necessary framework for the implementation and development of the PI project.

3.1. Steps taken and research methods

Design-science research requires the creation of an innovative artifact; and, in the case of PI, the artifact to develop is a Web application that includes a dynamic profile generation applied on VAAs, as presented in Section 5. The artifact belongs to a specified problem domain, which, in the case of the PI project, is how to extend classic VAA static profile including social media and sentiment analysis. Because the artifact is purposeful, it must also be useful in resolving the specified problem. Hence, a thorough evaluation of the artifact is crucial. In this work, the evaluation of the approach for dynamic VAA development is presented in Section 6.

Novelty is similarly crucial because the artifact must be innovative, solving a heretofore unsolved problem or solving a known problem in a more effective or efficient manner, for that reason, the following steps are conducted: 1) literature research (Section 2), and 2) theoretical framework development (Section 4). The former includes the design and implementation of three elements: 1) candidate answers (Subsection 4.1) collected via questionnaires sent to the presidential and vicepresidential candidates of the 2017 Ecuadorian national elections, 2) expert opinions (Subsection 4.2) collected from 24 experts invited to participate in the creation of candidate profiles, and 3) candidates Twitter feeds (Subsection 4.3) collected from each of the Twitter accounts of all presidential and vicepresidential candidates (Subsection 4.5).

In this way, design-science research is differentiated from the practice of design. The artifact itself must be rigorously defined, formally represented, coherent, and internally consistent. The process by which it is created, and often the artifact itself, incorporates or enables a search process whereby a problem space is constructed and a mechanism is posed or enacted to find an effective solution.

[4] http://myproductadvisor.com/

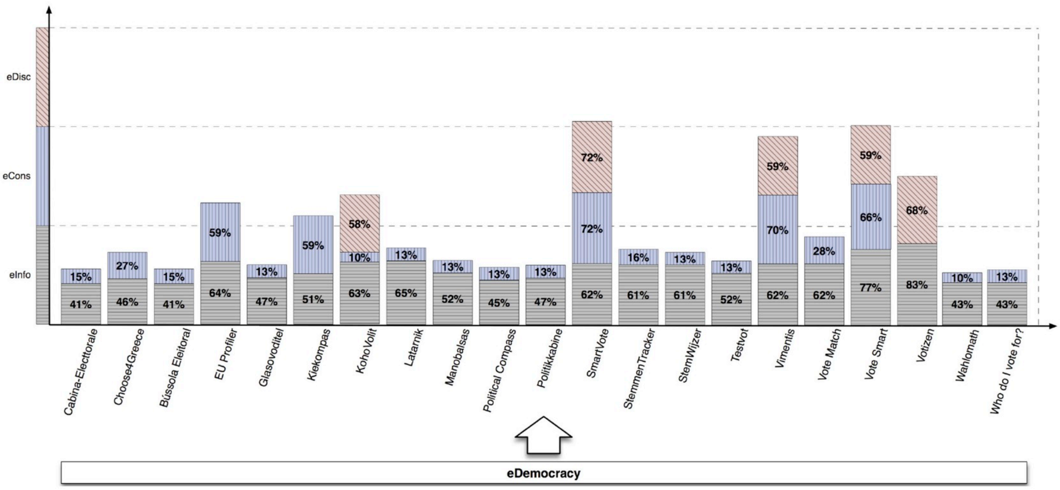


Fig. 2. Evaluation of Twenty One VAAs, adapted from (Terán & Drobnjak, 2013).

Finally, the results of the design-science research must be communicated effectively, both to a technical audience (researchers who will extend them and practitioners who will implement them) and to a managerial audience (researchers who will study them in context and practitioners who will decide if they should be implemented within their organizations). During the development of this work, various publications were generated and accepted by the academic community to support the artifact that was finally implemented in the case study of the 2017 Ecuadorian national elections (Terán & Drobnjak, 2013; Terán & Kaskina, 2016; Terán & Mancera, 2017b).

4. Dynamic VAA development

Designing and constructing candidate profiles are complex and essential task for providing recommendations to citizens. The main assumption in the creation of dynamic candidate profiles is based on the fact that, in most cases, the candidates are unwilling to answer the questionnaires proposed by the VAA developers. As mentioned in the previous section, in practice, two main methods are used to construct candidate profiles: using the answers of parties and/or candidates or the answers provided by experts (e.g., academics, journalists) about parties and/or candidates' political positions.

One example of a VAA in which the candidates' answers are provided is the *smartvote*[5] project. *Smartvote*'s success in engaging candidates to commit to providing their answers on the proposed policy statements comes from the long tradition of "direct democracy," in which Swiss citizens are confronted with elections and referendums several times per year (Hessami, 2016). As is mentioned in (Gasser, Gerlach, Thurman, & Staeuber, 2009), the authors show that, in 2003, about 50% of candidates submitted their answers to the *smartvote* questionnaire. In the most recent federal elections at the time of this study, 80–81% of candidates answered *smartvote*'s questions.

Unfortunately, the case of *smartvote* is complicated to replicate, given that, in most cases, VAA developers do not have access to candidates' answers and require expert opinions to construct candidate profiles. An example of this type of VAA is *EcuadorVota,*[6] which was introduced by the *PreferenceMatcher* consortium, [7] in which candidate profiles were constructed based on journalists' and political scientists' opinions. The parties' coding designs are presented in detail in (Geminis and Mendez, 2014) and use a Delphi iterative expert survey.

The project presented in this paper, (Participa Inteligente, 2016), uses a dynamic profile-generation approach introduced in (Terán & Mancera, 2017a). Unlike other VAA projects, the profile-generation method used by PI includes three elements: 1) candidate answers, 2) expert opinions, and 3) candidates' Twitter feeds. These elements are presented in Fig. 3 and will be mentioned in more detail in the next section.

4.1. Candidates' answers

The PI platform was designed to generate three types of profiles: candidate, citizen, and administrator. Candidate profiles were created by administrators to include the candidate's personal information, such as a photo, a section about the candidate, candidacy (i.e., presidential, vice presidential, national assembly, and regional assembly), political parties and coalitions, party logo, social networks (e.g., Twitter, Facebook, LinkedIn), curriculum vitae, studies, and experience.

Candidate profiles have limited privacy settings compared to a citizen profile. The limitations of candidate profiles are set as follows: creation and deletion of accounts, update of privacy settings, and update of Twitter accounts. Nevertheless, candidates have full access when interacting with other users on the platform, answering questions, posting articles, sending messages, and updating VAA questionnaires. PI's communication team approached all presidential and vice presidential candidates and invited them to use their accounts. The team's strategy was to create an initial profile of candidates based on declarations made in different media. The communication team designed the profiles and invited the candidates to update the initial profile. Formal invitations including the account credentials were sent out. A number of candidates accessed their accounts and used the platform to post articles, answer questions, and update their initial answers for the VAA questionnaire.

4.2. Expert opinions

The second element used by PI was the use of expert opinions. This approach was developed by the *PreferenceMatcher* consortium using *SmartCoding V1.0* for the Ecuadorian national elections.[8] The candidates' coding design is presented in detail in (Geminis and Mendez, 2014). A total of 24 experts were invited to participate in the creation of candidate profiles using *SmartCoding*. Each candidate (presidential and vice presidential) was assigned three experts in a blind configuration. The proposed approach included various rounds in which the experts

[5] *smartvote*: https://smartvote.ch
[6] EcuadorVota: http://www.ecuadorvota.com
[7] PreferenceMatcher: http://www.preferencematcher.org
[8] SmartCoding Participa Inteligente: http://preferencematcher.com/2016/ecu

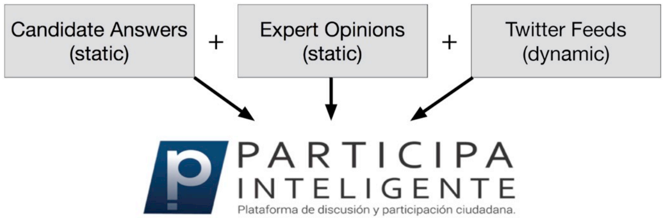


Fig. 3. Static and dynamic profile elements – PI.

could modify their answers to the VAA questionnaire and interact with other experts.

Nevertheless, given the nature of Ecuador's national elections and the time limitations for profile generation, only one round was completed and the final profiles based on expert opinions were included. The candidates registered officially at the Consejo Nacional Electoral, or National Electoral Council,[9] at the end of November 2016. The final list of candidates was presented at the beginning of December 2016, shortening the allotted time for candidate-profile generation via expert opinions.

Coders could provide five types of answers to each question in the VAA questionnaire: completely agree (CA), agree (A), neither agree nor disagree (N), disagree (D), completely disagree (CD), and no opinion (NOP). From the answers provided by coders, they could exhibit five patterns of coding, as shown as follows:

- **Complete agreement between coders.** This case is the simplest and most straightforward for coders. In this case, all agreed on a single answer (e.g., A, A, and A).
- **Largely agreement between coders by accident.** In a surprisingly frequent number of cases, one coder misinterpreted the direction of the question (e.g., A, A, and D). As an exaggerated example, two coders might have read the question as “soft drugs should be legalized,” whereas one coder read it as “soft drugs should NOT be legalized.” These cases are easy to figure out from the given justification, based on the other directions for the answer and the pattern of answering (e.g., CA, CA, and CD; A, A, and D). The moderators of *SmartCoding* are able to flag these cases and correct them.
- **Largely agreement between coders but not by accident.** These are cases like the ones described above or in a situation in which, for example, two coders answer A and one coder answers N. In these cases, the divergence between coders' opinions is genuine. The moderator will select one answer on the basis of the justifications provided or simply use an arithmetic method (e.g., arithmetic mean, median) to retrieve an answer that takes into account all codings. It is important to bear in mind that arithmetic methods depend on what the VAA platform will allow for coders, including the confidence factor that can unbalance the disagreement.
- **Largely incomplete coding.** In these cases, one of two things may have happened: Either one coder found something that the other coders did not and this person is correct, or this coder mistakenly assigned a position that does not exist (e.g., CA, NOP, and NOP; CA, N, and N). The coder could have taken something out of context, or the candidate said one thing at one time and a different thing at another time, but the coder only saw the first instance. In these cases, it is difficult to have an automatic way to solve this inconsistency. One solution for these cases is that the moderator will pick an answer on the basis of the justifications provided by the coders.
- **Complete divergence between coders.** Here, the different codings reflect a confused position on the part of the candidate or maybe a confusing question (e.g., A, N, and CD). To illustrate this problem, the example may contain unknown or contested terminology. For instance, compare “drugs should be legalized” with “soft drugs should be legalized” and â€œcannabis should be legalized.â€ In these cases, the moderator can select an answer on the basis of justifications or alternatively assign an NOP answer; however, if more than two candidates get an NOP assignment, omitting the question altogether is recommended.

4.3. Candidates' twitter feeds

This study's authors believe that the pillar of a VAA design should be based on a resistant or resilient candidate-profile model that can tolerate the answer or user manipulations in order to represent the most accurate information, ideas, and political orientations of candidates or political parties. The definition of a candidate-profile model is crucial during elections. It reflects the political parties' and/or candidates' orientations and goals as a whole. In this section, the different elements that can define a candidate profile and explain the criteria behind all these characteristics are shown. In (Terán & Kaskina, 2016), two components of a profile generation for VAAs static and dynamic are included to accommodate policy statements ($I_1, \ldots, I_n$), context awareness (CA), privacy settings (PS), user interaction (UI), and sentiment analysis (SA). These elements are presented in Fig. 4.

In this work, the VAA 1.0 (candidate answers and expert opinions) together with the SA block of the VAA 2.0 are implemented using candidates' Twitter posts. The combination of both categories (static and dynamic) is a good basis for a candidate-profile template that can represent all of the factors involved in the candidate's political environment. The reason to use an SA block is the so-called cold-start problem. At the moment of the development of this project, Twitter was the only source of data available. However, future work should explore the implementation of more elements.

4.4. Dynamic elements

In PI, the candidate model has two main parameter categories, static and dynamic Fig. 5 shows the construction of a vector profile for the candidates by correlating all the parameters; it shows the social topic categories ($I_1, \ldots, I_6$), which are mapped into three vectors of 50 elements or dimensions (policy statements). The candidates' dynamic profile vector, presented in Fig. 5, includes three elements: static vectors from experts, static vectors from candidates, and SA block using posts of candidates in the social network Twitter. Additionally, average and importance vectors are considered to obtain a dynamic profile vector for each candidate.

The sizes of the vectors are based on the questionnaire regarding different policy statements provided by PI, and each dimension is represented by a question. For simplicity, an average value between the static and dynamic elements is taken, and the weight, which is related to a current social-topic context, is represented by an importance factor vector ($\alpha_1, \ldots, \alpha_6$) that will determine which dimensions of the vector become more important in certain periods of time.

The importance factor vector, which consists of α values, has a scale from 0 to 1, with 0 representing low importance and 1 representing high importance. To illustrate the use of α, consider, for instance, an economic crisis mid-election. In this case, the social topic of the issue “economy” should be weighted with a higher importance, $\alpha_1 = 1$, and perhaps the rest of the social topics ($\alpha_2, \ldots, \alpha_6$) should be weighted with 0.5. This will give more influence to the questions related to the economic issue in the dynamic profile vector. In the PI platform, the weight factor α has a default setup of 1 for all social topics. Thus, all elements are considered equally important. In the subsequent sections, more details are provided to explain the construction and use of this vector in our analysis.

[9] CNE: http://cne.gob.ec

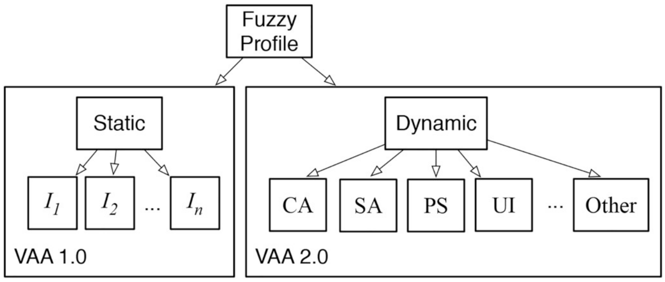


Fig. 4. Profile generation for VAAs, adapted from (Terán & Kaskina, 2016).

Fig. 5 shows the SA vector of 50 dimensions. The SA block can be applied to many social networks. In this work, the SA block is based on the postings of presidential and vice presidential candidates on the social network Twitter during the campaign period.

The profile generation considers three main vectors, which are explained as follows: (a) $\overleftarrow{C}$: the candidate vector has the direct answers values of the questionnaire applied to them, (b) $\overleftarrow{E}$: the expert vector has the direct answers values of the questionnaire applied to them, and (c) $\overleftarrow{SA}$: the SA vector contains the answers to the questions based on the opinions or mentions of the candidate in his/her social network.

The vectors share the same length or dimensions and are proportional to the length of the questionnaire used in the VAA. In the case of the PI project, the vectors have a length of 50 questions or dimensions. It is important to mention that each of the vectors contains different subsets of values, which correspond to the social categories: economy, social welfare, international affairs, etc. Algorithm 1 shows the computation of the candidate profiles.

Algorithm 1 Profile vector algorithm.

1: Set the $\overrightarrow{IV}$ with priorities and value of α between (0,1)
2: **loop**
3: Obtain the values of the vectors: $\overrightarrow{C}$, $\overrightarrow{E}$, and $\overrightarrow{SA}$.
4: Compute an average vector: $\overrightarrow{AvgVector} = (\overrightarrow{C} + \overrightarrow{E} + \overrightarrow{SA})/3$
5: Compute the Profile Vector (PV): $\overrightarrow{PV} = \overrightarrow{AvgVector} * \overrightarrow{IV}$
6: **end loop**

4.5. Data set collection

PI was officially launched in the three main cities of Ecuador (Quito, Guayaquil, and Cuenca) as part of a communication campaign in different universities (ESPOL, 2016; UDLA, 2016; Universidad de Cuenca, 2016). The communication group of PI contacted all candidates to join the platform and to answer the questions proposed in the VAA. Some of the candidates provided their answers and used the platform tools. As mentioned in the previous section, the data sets used in the dynamic elements of the VAA were generated from each of the Twitter accounts of all presidential and vice presidential candidates. These data sets are accessible (Participa Inteligente, 2017).

4.5.1. Preprocessing of the twitter data set

For the dynamic element of the candidates' profiles, a Python script was created to collect, transform, and filter the data obtained from Twitter to be used later by the SA block. The script could also remove unnecessary data. The preprocessing involved four steps:

- **Step 1:** The tweets of candidates were collected directly from the candidates' profiles and saved into a text file. Nevertheless, one of the limitations was that Twitter's policy allows the retrieval of only

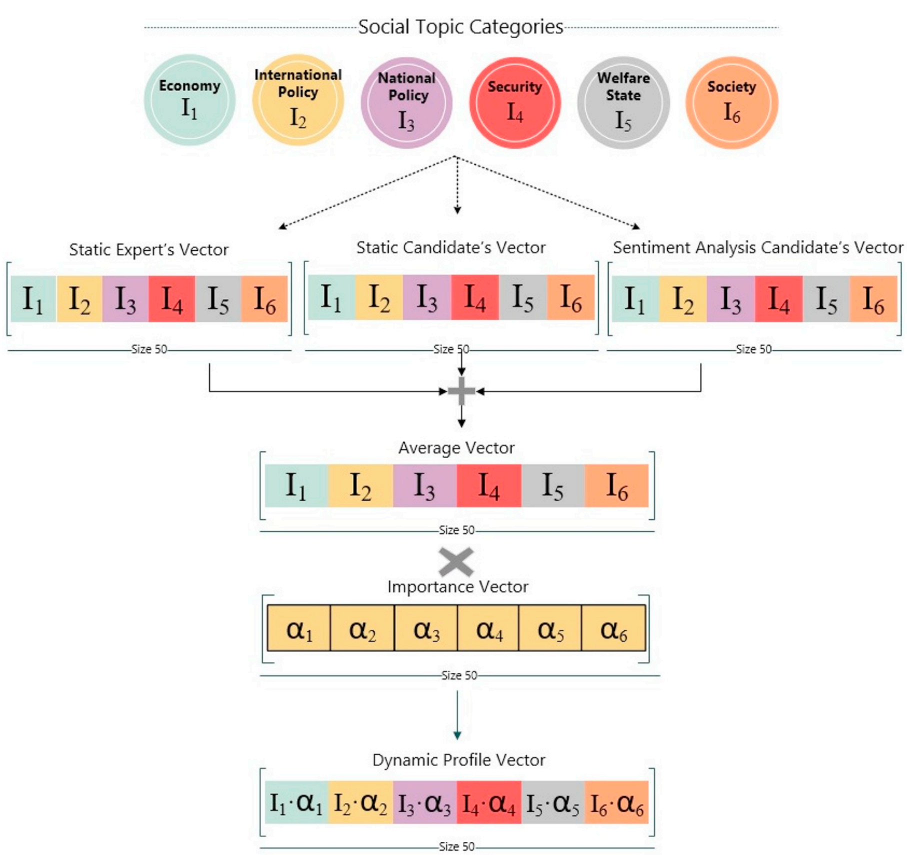


Fig. 5. Dynamic profile vector of candidates construction, adapted from (Terán & Mancera, 2017a).

the last 3200 tweets from a user. For that reason, this process was repeated when the candidate was close to publishing more than 3200 statuses or every two weeks, and repeated tweets were removed.

- **Step 2:** Once the tweets were collected, the URLs shared by the candidates were removed since they did not offer any relevant information.
- **Step 3:** Emoticons and photos were also removed from the tweets, as well as all Spanish stop words.
- **Step 4:** The last step was to add each tweet into a Python dictionary with an identification number (id), timestamp, and its text. Finally, all the dictionaries were sorted by their timestamps and included into a data frame.

4.6. Sentiment analysis

PI considered Twitter, which is a micro-blog social networking service that enables users to publish and read short 140-character messages (in late 2017, the limit was extended to 280 characters), to perform SA in the creation of candidates' profiles. The advantages of this social media platform are that all the posts are public and that it is possible to recall them via the API.

4.6.1. Sentiment analysis elements

In this section, the categories that are considered part of the SA architecture and their interconnections are presented in Fig. 6. The SA block considers two main categories that are involved in the construction of the dynamic part of the candidates' profiles:

- **Candidate Posts:** Posts that candidates retweet or write personally on their accounts.
- **Candidate Tags:** Comments from other Twitter users (voters) in which the candidates are referenced.

The next step is to compute the so-called SA candidate vector (*SACV*) using an importance vector (*IV*). This approach is presented in Eq. 1 (Terán & Mancera, 2017a).

$$SACV = \sum_i A_i IV_i a + B_i IV_i (1 - a) \tag{1}$$

The SA candidate's vector is built from the sum of the two main categories (candidate tags and candidate posts), which are mapped between the tweets and social categories. Eq. 1 represents the calculation of the dynamic candidate's vector. The value a is an importance variable between 0 and 1. To illustrate the use of this variable, assume that $a = 0.3$; in such a case, the importance of the candidate's posts is set at 30%, and the importance of the tags from the users is set at 70%. This allows a more realistic scenario in which to create a vector that represents the voters' perception of candidates. However, the value of a can be changed in further studies in order to give more or equal importance to the vectors involved.

A tweet's capture is performed with Python so that the words in each candidate's tweets can be read and counted. Later, a Spanish SA dictionary combined with human analysis is needed to understand the full context of the tweets and verify the values assigned to each of the vectors' dimensions.

As was mentioned before, the value of a ensures that the two main categories do not have the same relevance. For instance, the candidates' posts might be fictitious or manipulated in order to maintain the candidate's good image, so this factor can be biased in favor of the candidate. However, the posts or tweets in which the candidate has been tagged are more representative. Nevertheless, external users still pose a problem by working cooperatively to affect a candidates' public image by posting compromising messages or activating an Internet bot. In practice, the PI platform used a value of $a = 0.5$ in order to provide equal importance to both categories in the profile.

At the end of the process, the SA model determines whether a user who tagged a candidate is authentic by observing his/her number of followers. It is assumed that most Internet bots do not have followers because the accounts are fake and are automatically created. However, finding an ideal method to avoid this potential bias is out of the scope of this work. Finally, the *SACV* is calculated periodically at around every

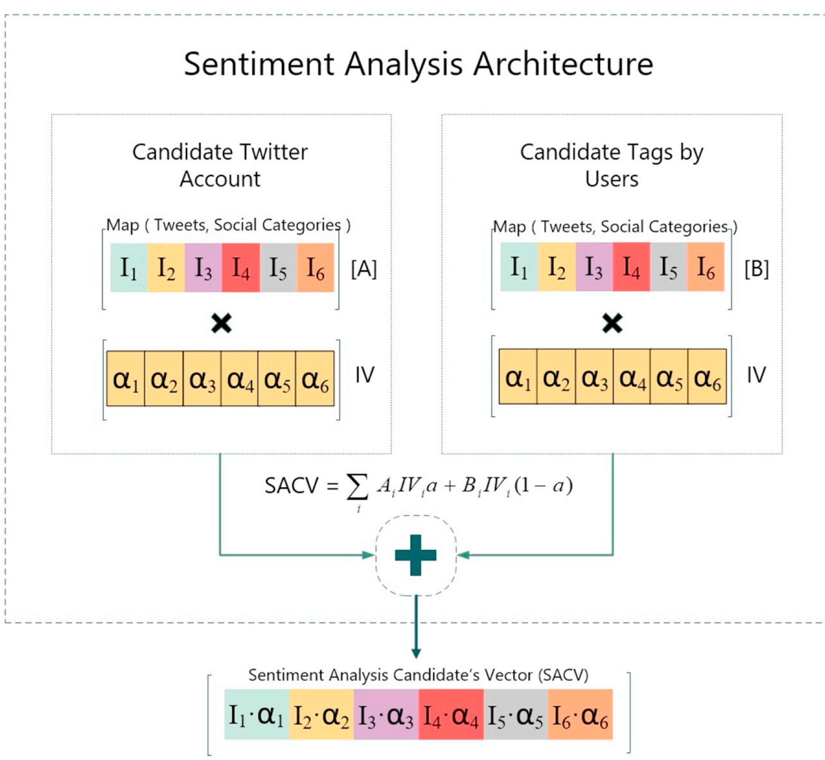


Fig. 6. SA architecture, adapted from (Terán & Mancera, 2017a).

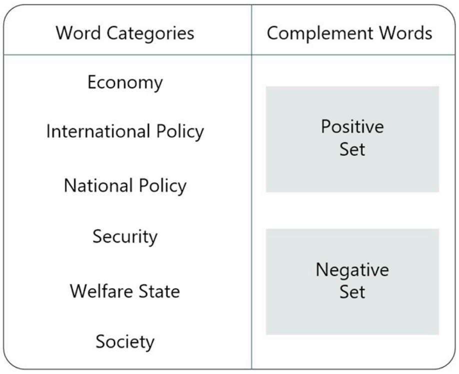


Fig. 7. Spanish SA structure.

3200 Twitter status updates per candidate; the collection of the candidate tags by user data is run at the same time as the collection of the tweets of the candidate in a 10-min time frame, due to the amount of traffic generated by retweets or tags. Algorithm 2 shows the computation of the SA profile vector.

Algorithm 2 Sentiment analysis profile vector algorithm.

1: Set the important vector $\overrightarrow{IV}$ based on priorities
2: Set the value of a between (0,1)
3: Set all the values of $\overrightarrow{SA}$ in neutral.
4: **loop**
5: Collect post from candidates in their social network and candidate tags in other posts
6: Clean posts and tokenize words
7: Generate pairs of words with an adjective and a noun
8: Compare the pairs against a sentiment analysis dictionary and obtain a rank
9: Is one of the pairs relevant for updating the vector?
10: **if** Yes **then**
11: Update the vector in their corresponding the social category block
12: Calculate: $SACV = \sum_i A_i IV_i a + B_i IV_i (1-a)$ (Equation 1)
13: **else**
14: Go to step 5
15: **end if**
16: **end loop**

Table 2
Equivalence weight between the Spanish SA and AFINN dictionary.

Labels	Spanish sentiment dictionary (Weights)	AFINN dictionary (Weights)
Strongly disagree	-1	$\{-5, -4\}$
Disagree	-0.5	$\{-3, -2\}$
Neither agree nor disagree	0	$\{-1,1\}$
Agree	0.5	{2, 3}
Strongly agree	1	{4, 5}

4.6.2. Spanish dictionary for sentiment analysis

One of the main challenges of doing SA in the Spanish language is the absence of a dictionary; for that reason, creating a Spanish dictionary was required. Another problem is that the Spanish language including local wording, dialects, and expressions that are unique to the region varies in different regions. SA construction involved five stages and used the AFINN-96 dictionary (F. Ǻ. Nielsen, 2011), which contains 1468 unique words and phrases on 1480 lines, as a ground vocabulary. Fig. 7 shows the SA dictionary structure separated by two main sets, word categories and complement words. The creation of the SA Spanish dictionary is described as follows:

- **Literal AFINN-Spanish Translation:** A RAW translation from English to Spanish was used to create the first template.
- **Score Correlation:** The AFINN dictionary has its own word weights, which were mapped according to the values shown in Table 2.
- **Repeated Words:** The AFINN dictionary has many repeated words, especially after translation into Spanish. Hence, many words were removed, and the dictionary size was reduced from 1468 words to 350 Spanish words.
- **Word Categorization by Social Topics:** One word can belong to one or more categories. Hence, all the words were manually labeled as belonging to one or more categories.
- **Addition of New Words:** Ecuador has three main regional variants: Equatorial Pacific Spanish, Andean Spanish, and Amazonian Spanish. Thus, new words were added manually based on the forum discussions and tweets in which users reference candidates.

4.6.3. Sentiment analysis implementation

SA block implementation consists of five main stages; four of them are computed automatically, and one requires human intervention, as shown in Fig. 8. It has five main built-in stages: (1) preprocessing, (2) matching, (3) category mapping, (4) sentiment-vector creation, and (5) human verification. These stages are described as follows.

Tweet Preprocessing. The fetching of the tweets for the implementation of SA was performed through a series of Python scripts that preprocessed the information in four main steps:

- **Stage 1:** Fetching candidates' tweets directly from their profiles and saving them in a text file.
- **Stage 2:** Removing the URLs shared by the candidates because the URLs do not offer any relevant information.
- **Stage 3:** Filtering out emoticons, photos, and stop words in Spanish from the tweets.
- **Stage 4:** Adding each tweet into a Python dictionary with an identification number, a timestamp, and its text. Finally, all information is converted into a data frame.

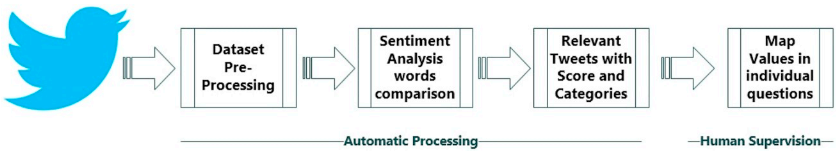


Fig. 8. SA implementation process.

Matching and Categories Mapping. Matching and Category Mapping. For every tweet, a minimum of two keywords must be contained in the SA dictionary (one in the word category and the other in the complement-words category) as shown in Fig. 7. Guillermo Lasso's tweet from 29.03.2017 (Fig. 9) is used as an example throughout the rest of the paper. After the tweet is processed, it will contain many isolated words. However, the text matching will identify key words such as *salud*, *educacion*, *gratuita*, *calidad*, *campaña*, and *sucia*. The matching selects the words that belong to a word category in the SA dictionary. In this particular case, the words *salud* and *educacion* belong to the welfare-state category. The words *gratuita*, *calidad*, and *sucia* need to be classified in the complement-words block with their respective sentiment scores. As an example, we have a positive set –*gratuita* (5) and *calidad* (4)– and a negative set, *sucia* (5).

The word *campaña* was not found in the dictionary, so it was discarded. At the end, the tweet gets a mark based on the positive and negative sets and their values in the dictionary. In this case, by adding the sentiment (weights) of the words in the dictionary and in general by using cancellation, a positive mark of 4 was given to the word *calidad*. Thus, the tweet has a positive mark in social welfare. As the tweets are ranked by their sentiment scores, they are classified in the social categories. Thus, each category will have a certain degree of positive or negative sentiment per candidate. It is important to highlight that this rank per category will affect the weight of all the questions related to a particular social topic. Table 3 shows the social-category ranks.

Sentiment-Vector Creation. In order to compute the dynamic sentiment-vector profile for each candidate, it is necessary to adapt the weights of all the questions in each category. Based on the survey provided in the platform, which contains 50 questions, a neutral vector of 50 dimensions is created with default values of 3 (Neutral). As an example using the values of Table 3, if the candidate Guillermo Lasso has a score of 4 in the welfare-state category, Lasso's rank for all related questions will increase. In this particular case, the new score for the question related to welfare is on average $(4 + 3)/2 = 3.5$. Thus, the dynamic candidate-profile vector would look as if the welfare-question positions are full of values equal to 4. Nevertheless, it is important that this process is done iteratively for every important tweet that reaches this state.

Human Verification. Although the tweets have been scored using SA, humans need to read only the classified and scored tweets to determine the context in which the tweets were created to verify the individual questions that are affected. In a continuation of our previous example, not all questions in the welfare category mention education and health; thus, only those are affected, and the rest are corrected. After a series of iterations, including coordination between human supervision and SA computation, the last-computed dynamic vectors for all candidates are shown in Table 4.

An evaluation of the accuracy of the dynamic versus static elements of candidate profiles is presented in Section 6.

Limitations. Although SA allows the automatic processing of most of the tweets, some limitations of the approach should be mentioned:

- **Keywords Match:** The two-keyword approach in many cases matches one word from the complement-word set of the dictionary, but it fails in 60% of the cases to find a partner keyword in the word category set. This could be due to the constant personal attacks between candidates.
- **Human Intervention:** Despite the effort to introduce an automated solution using SA, it was not possible to avoid the need for human intervention in determining the context of relevant tweets and mapping them to one of the 50 questions.
- **Spanish SA Dictionary:** The dictionary developed was an approach to mapping words from the candidates using political vocabulary and local dialects from Ecuador. Unfortunately, it is still considered to be weak because of the small number of relevant words. Future implementations should consider expanding the dictionary to include more relevant and unique words.
- **Twitter-Tag Streaming:** Twitter limited the time for the streaming capture, and the performance of proper monitoring was also limited. Twitter may implement a control mechanism to avoid the misuse of resources using the API interface.

5. Dynamic VAA implementation

PI is a research project that was introduced in the context of the 2017 Ecuadorian national elections as a way for citizens/voters to discuss public-policy issues. In the classical VAA, neither the candidates nor the voters can generate content (i.e., questions, answers, comments), but in the PI-proposed VAA 2.0, both candidates and voters can create different types of content. With the inclusion of so-called dynamic profiles and the allowance of users to become content generators (Terán & Kaskina, 2016), the intent of the RS approach described in this work is to improve the profile generation of candidates who, in most cases, do not answer the questionnaires proposed by VAAs, requiring that their profiles be constructed based on expert opinions.

PI includes a number of tools such as recommendations of candidates (VAA); user-account management (e.g., privacy settings, vote intentions, and reputation); creation of thematic groups, posts, and questions for the community; private messages; articles; and others. The platform-provided recommendations are defined as a personalized RS. Nevertheless, this paper focuses only on the VAA, the interfaces designed to collect answers from users (candidates and citizens), and the recommendations provided to citizens for candidates that closely match the citizens' profiles. The interfaces developed for the VAA within PI are presented in Fig. 10.

As part of the profile generation, PI collects Twitter feeds from general-election candidates as well as feeds from registered users (noncandidates). It allows users to identify the candidates for president and vice president and includes a filter for each of the proposed political issues: the economy, public policies, society, international policies, security, and education (Fig. 10). As was mentioned in the previous section, PI was developed as a social network for participation through discussion. It allows users to create their own profiles and customize their communication, posts, and visibility preferences. For VAA data

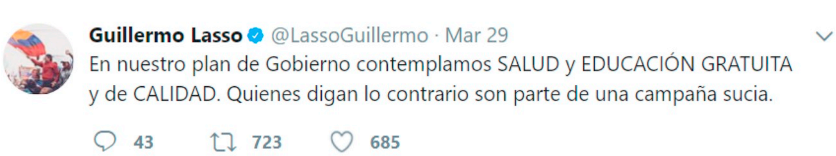


Fig. 9. Guillermo Lasso example tweet.

Table 3
SA social topic evaluation vector.

Candidates	Economy	National policy	Society	International policy	Security	Welfare state
Guillermo Lasso	5	4	4	3	4	4
Cynthia Viteri	4	3	5	4	3	4
Lenin Moreno	4	3	5	3	4	3
Paco Moncayo	4	5	4	3	3	3
Abdala Bucaram	4	5	5	3	4	3
Patricio Zuquilanda	5	5	4	4	3	4
Washington Pesantez	4	5	3	3	3	3
Ivan Espinel	4	4	5	3	3	4

Table 4
Final dynamic candidates' vectors.

Candidates	Dynamic vectors
Guillermo Lasso	[3,3,2,3,4,2,3,2,2,2,2,3,3,3,2,3,2,4,3,3,2,3,3,4,2,2,2,3,3,3,3,4,2,2,3,4,3,3,4,3,3,3,3,4,3,4,1,2,2,2]
Cynthia Viteri	[3,3,4,3,3,2,3,3,3,2,2,2,3,3,2,3,2,3,2,3,3,3,3,3,3,3,3,3,2,2,3,4,3,2,3,3,3,3,2,3,4,3,1,4,1,4,2,3,2,3]
Lenin Moreno	[4,4,4,3,3,2,2,2,1,2,2,2,3,3,3,3,3,3,2,2,2,4,3,3,5,5,4,2,3,3,1,2,2,2,3,4,2,3,3,3,3,2,2,1,3,3,3,3,3,3]
Paco Moncayo	[4,3,4,4,2,2,1,2,3,3,3,3,4,4,4,3,2,2,1,1,2,3,2,3,4,3,3,3,2,2,1,1,3,3,3,4,2,3,3,4,2,1,2,3,2,2,2,3,3,4]
Abdala Bucaram	[3,3,3,3,3,1,3,4,2,2,2,3,3,4,3,4,4,2,3,4,4,2,3,3,2,2,2,4,4,3,4,3,3,3,2,2,4,4,3,3,3,4,3,4,3,3,3,4,3,2]
Patricio Zuquilanda	[3,3,3,3,3,3,3,3,3,3,3,3,3,3,2,3,3,2,3,3,3,3,3,2,2,3,3,2,3,3,3,2,3,3,3,3,3,3,3,3,3,2,3,4,3,2,2,2,3,2]
Washington Pesantez	[3,3,2,3,3,2,4,2,3,2,3,3,3,2,3,3,3,3,3,3,2,2,2,2,3,2,2,3,3,2,3,3,3,3,3,3,2,3,2,2,3,4,3,3,2,3,2,2,2,2]
Ivan Espinel	[3,3,3,3,2,3,2,3,3,3,3,2,3,3,4,3,3,3,3,2,3,3,3,3,2,4,4,2,4,3,2,3,3,2,3,1,3,3,3,3,3,3,3,3,3,3,2,3,3,3]

collection, which is the main focus of this work, the interface developed includes additional features that are not presented in classic VAAs.

A VAA, the data-collection interface developed for the PI, gives users the options to navigate the different proposed political issues (economy, public policies, society, international policies, security, and education) within the same interface, to answer or update their questions at any time (even if they decide to quit the session), and to use a set of emoticons intended to capture the user sentiment regarding each question (Fig. 10a). In addition to the implemented navigation, each question features a link that includes additional information regarding each question in the form of text, images and/or videos along with the option to add comments or ratings and discuss each of the questions proposed in the VAA.

The interface for recommending candidates in the VAA was designed to provide a graphical representation of the positions of all candidates running for president and vice president with respect to the user profiles. It requires that a minimum of 30 questions from a set of 50 questions be answered, sending an alert to the user to indicate the number of questions needed to provide a graphical recommendation. This required minimum number of questions is intended to minimize the effect of a voter having few concordant positions with all candidates. Additionally, the interface allows users to compare their affinities to those of each candidate in terms of each of the political issues proposed, or all of the statements can be viewed at the same time. 10b shows an example of the navigation along the different political issues.

6. Evaluation

This section describes the evaluation of the recommendation algorithms that were implemented as part of the PI project. In consideration of the characteristics of the three types of evaluation mechanisms used within the academic literature, which are mentioned in the previous sections, the evaluation will focus solely on measuring the project's predictive capacity (see subsection 6.1) and the users' perceptions of the recommendations received and the usability of the platform (see subsection 6.2).

6.1. Offline evaluation

Precision in prediction is considered the most commonly used evaluation metric in the recommendation-system literature. This allows the prediction of the users' opinions on the elements to be recommended or the users' opinions on the elements' probability of use, in the case of the consumption analysis of recommended products. For this case, it is assumed that the way in which the items are presented is not considered in the evaluation; instead, only the ability of the system to understand the preferences of the user is considered.

One of the metrics most commonly used to measure the accuracy of the system's prediction capacity is the so-called root mean squared error (RMSE) (Gunawardana and Shani (2015)). RMSE is shown in Eq. 2

$$RMSE = \sqrt{\frac{1}{\alpha} \sum_{(u,i)\in\alpha} (\hat{r}_{(u,i)} - r_{(u,i)})^2}, \tag{2}$$

where $\hat{r}_{(u,i)}$ represents the prediction of calculated preferences and $\hat{r}_{(u,i)}$ is the users' known preferences for a test set α of the ordered pairs' user item (u,i).

6.1.1. Preparation of the data set for offline evaluation

To perform the evaluation (offline) of the algorithms implemented, it is necessary to simulate an online process in which the system makes predictions or recommendations. In order to achieve this objective, user data are used, and then some of these interactions/evaluations are eliminated in order to simulate how the user would qualify a specific article and compare it with the predictions made by the system. To evaluate the dynamic political profile developed within the PI project, the following assumptions are made:

- There is no access to ground-truth data to evaluate the accuracy of the recommendations due to the nature of VAAs, voting, and elections processes, which are unique events, and because the political issues will vary from election to election.
- The accuracy is compared between the dynamic elements of candidate profiles and the static ones (candidate answers and expert opinions).
- The results provided by accuracy metrics can only be interpreted as divergence between the three elements being compared (candidate answers, expert opinions, and Twitter) and can lead to conclusions regarding the level of concordance between different information sources.

6.1.2. Results

The three elements that are used for the evaluation are (1) expert vectors (EV), (2) candidate vectors (CV), and (3) SA vectors. Fig. 11

(a) Collection of Answers (b) Recommendation of Candidates

Fig. 10. GUI of VAA developed for PI, 2017.

shows the results of applying RMSE to the pairs: EV vs. DV, CV vs. DV, and CV vs. EV.

The results presented show the level of divergence between each element of the profile generation. Nevertheless, this behavior differs from candidate to candidate, and one can explain it by looking at different factors, including the social network Twitter and a lack of the information needed for an expert to complete the profiles. These results can lead to a more precise and in-depth study of political behavior versus public perception; nevertheless, this is out of the scope of this work.

6.2. User-centered evaluation

To analyze and evaluate the impact of the PI platform, a survey was conducted after the commission for the 2017 Ecuadorian national elections declared the official results. The survey was developed to understand user perceptions and levels of satisfaction for the different tools implemented in the platform. A total of 602 users were contacted for the evaluation, and 63 answers were collected in a period of five weeks (from June 4, 2017, to July 10, 2017). The complete evaluation included a total of 28 questions divided into six categories: impact, user perception, VAA usability, e-collaboration, privacy, and user satisfaction. The results regarding the VAA implementation are presented in Fig. 12; they show three answers from the complete survey regarding: platform usability (Fig. 12a) and VAA accuracy (Fig. 12b).

7. Discussion

This work focuses on the study of VAAs, which are a type of RS, to recommend candidates and parties to citizens during voting and elections. VAAs are based on static profiles generated by VAA designers through two main methods, from the direct answers of candidates (i.e., the *smartvote* project) or with the help of experts who answer the questionnaires designed for a specific election or voting process (i.e., the *PreferenceMatcher* consortium). In the second type, experts answer for each candidate and use a particular method until they reach consensus. These two methods are considered static because they cannot be modified or updated once the profiles of the candidates are completed.

In particular, the proposed approach corresponds to the design and implementation of the so-called dynamic profile generation of candidates, which uses a participatory platform that allows citizens to not only receive recommendations but also become content generators. The main contributions of this work are listed below:

The PI project was developed from an academic perspective as a channel for citizens' discussion and participation. Nevertheless, many people are engaged in a big discussion on the role and position of independent research and academics in debates of public interest. The Cambridge Analytica scandal (The Guardian, 2018b) regarding the use of Facebook data and targeted advertisements to influence elections in the digital age is raising a big question on the independence of academics in political issues (Laterza, 2018).

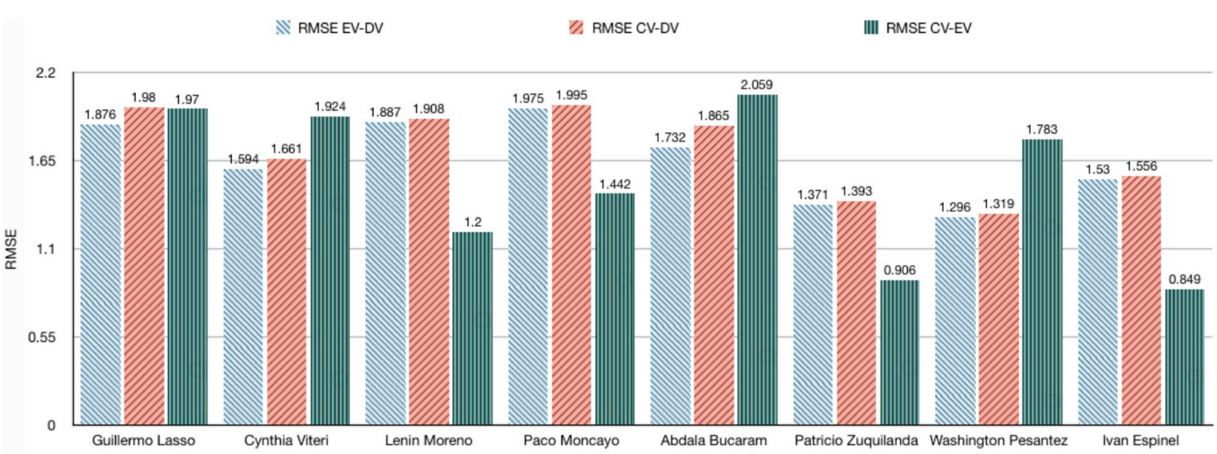
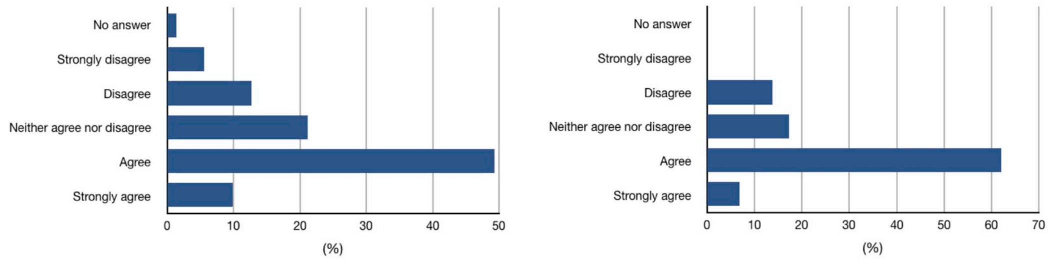


Fig. 11. Evaluation profile generation: EV vs. DV, CV vs. DV, and CV vs. EV.



(a) Do you consider that the platform was easy to use? (b) Do you consider that accuracy of the VAA was according to your expectations?

Fig. 12. User-centered evaluation – PI.

The use of personal data, especially with the use of technology and smart systems, is an important factor that needs to be considered to enhance democratic processes that need to be just that, democratic (Common, 2018; Edwards, 2018). In the work of Tarran (2018), the author mentions that, according to Christopher Wylie, Cambridge Analytica "exploited Facebook to harvest millions of peoples' profiles and used that data to target voters with personalized political adverts" (The Guardian, 2018a).

On the other hand, the spread of so-called "fake news" in social media platforms is generating a large impact on decision-making and the perceptions of societies. Social media platforms such as Facebook have different structures than those of classic media and communication channels (e.g., TV, newspapers, and radio). Content can spread among users with no filtering, fact-checking, or editorial judgment. An individual with no track record or reputation can in some cases reach as many readers as other media channels can (Allcott & Gentzkow, 2017).

Likewise Facebook, PI promotes actively participation of users and it can become a target for misinformation inside of the social network. Thus,it is important that projects such as the PI are developed with the main objective of enhancing transparency and provoking societies to discuss their problems and needs in a participative fashion with the use of technology. These are important objectives that the academic community needs to tackle, not only for research purposes but also for the purpose of providing better tools for citizens that can lead to better-informed decision-making.

8. Conclusions, scientific contributions, implications, limitations and future work

8.1. Conclusions

This study represents the first of its type to present a dynamic VAA implementation, which provides personal recommendations to users instead of providing a general recommendation. In terms of acceptance, not only the Ecuadorian academic community was welcoming the platform but also general users. Based on the evaluation, most of the users are willing to continue using the platform and would recommend it to others. The users of PI also declared that they did not consider the platform difficult to use. This confirms also the findings of Hong (2013) about the benefits of using social media in political campaigns.

The platform offered meaningful results and new insights into the relationship between voters and candidates. Nevertheless, new questions were raised that can be part of future studies: What is the right level of granularity for survey questions? Could a SA block be more effective if more parameters were considered? What are the potential changes in perception that could occur when more elements are added to the candidate profiles? This work provides an ideal basis for future research in the area of VAAs and their interfaces; nevertheless, it opens up a broader spectrum of applications for policymakers including decision-making, collaborative working environments, fuzzy voting, and eEmpowernment (Hong, 2013; Loukis, Charalabidis, & Androutsopoulou, 2017; Sobkowicz, Kaschesky, & Bouchard, 2012).

8.2. Scientific contributions

The main contribution of this work is related to the use of sentiment analysis with microblog data to enhance the profile generation of VAAs. In this work, the methodology to design a dynamic candidate profile and its application on a real case study is presented. Unlike other VAA projects, the profile generation that PI uses includes three elements: (i) candidate answers, (ii) expert opinions, and (iii) candidates' *Twitter* feeds.

In this study, the main assumption is that the pillar of a VAA design should be based on a resistant or resilient candidate profile model that can tolerate the answer or user manipulations to represent the most accurate information, ideas, and political orientations of candidates or political parties. The definition of a candidate profile model is crucial during elections, as it reflects the political parties'/candidates' orientations and their goals as a whole.

Although this approach presents many advantages, it also has disadvantages. For instance, if a candidate does not have enough interaction in social platforms with users or supporters. Therefore, the more information the voters and candidates can provide, the better the profile will generated. Future work should also include other sources of information including an additional element using collaborative filtering methods using the opinions of the crowd about political profiles.

The practical output of this project was the introduction of a smart social network to enhance citizens participation and discussion. The platform included several sections and features to provide information to the users (e.g., discussion forums, statistics, candidate's *Tweets*, and personalized RSs). Different research communities can conduct studies using the datasets generated within PI platform.

8.3. Implications

Social networks applications such as PI, where users, policymakers, experts, politicians, and voters, are part of the discussions could have a positive impact in the level of participation. Policymakers could get involved when there is a social platform that exposes their profiles and ideas to the public. This interaction can close the communication gap and creates a sense of awareness about the problems in the society as mentioned in the work of Hong (2013).

The SA block included as a part of the dynamic profile of candidates challenge the controversy between actions and thoughts. It is a mining technique that empowers citizens to be reactive to government policies, provisions, or candidates ideologies as it was also mentioned in the work of Staci, Zavattaro, and Edward French (2015).

Even though PI was developed for the discussion and participation in election campaigns, it can be applied on different contexts besides the analysis of political discourse (Vepsäläinen, Li, & Suomi, 2017; Yaqub, Chun, Atluri, & Vaidya, 2017). Policymakers, politicians, and experts in different fields can find a high value in platforms such as PI, that provides different types of recommender systems using SA, not only as part of the VAA but in other applications including, for example, project proposals, conversations, profiles, and decision-making processes, among others (Panagiotopoulos, Bowen, & Brooker, 2017). Policymakers can have indicators of citizen opinions allowing them to have concrete information on the impact of a policy or political statement, allowing them to react on societal challenges.

The SA block is considered as neutral moderator in which users rely and trust. As a consequence, it encourages politicians and experts to be honest, clear, and transparent in their communication skills within social networks to enhance their public image and credibility (Ussama, Soon Ae, Vijayalakshmi, & Jaideep, 2017).

8.4. Limitations

During the implementation phase, one of the limitations was the generation of a sentiment analysis dictionary in Spanish language (more details at the end of subsection 4.6.2). It was implemented by translating an existent English version (F. Ǻ. Nielsen, 2011). Spanish language has different variants of words depending on the cultural context. In this work, the dictionary was manually reviewed and contained 1′468 unique words and phrases on 1′480 lines, as a ground vocabulary (refer to Fig. 7), which still can not cover all word combination semantics.

The use of Twitter, as a data source, was assumed as the main communication channel of candidates. This may not be enough to represents the ideas and position of the candidates. Future work should include other data sources or discussion channels; nevertheless, social networks, such as Facebook or Instagram are not so flexible in terms of data access as Twitter, where posts of the users are public and accessible via an API.

In terms of data completeness and engagement, the platform allowed users to interact and answer some questions to provide personal recommendations. The more information provided, the better the recommendation. However, from all users that registered within the platform, only a small set, around 118 were able to interact with the dynamic VAA developed. This gives the minimum necessary information to provide meaningful results in terms of recommendations. The small number of registered users was also due to the short period of time for the campaign of the 2017 Ecuadorian national elections.

8.5. Future work

There are two perspectives on scaling the PI project. The first perspective is technological and includes the implementation of mobile applications, the enhancement of existing modules, visualization, and an increase of the processing capacity of our servers. The second perspective for scaling is regional, which includes running the platform in different countries and cooperating with other research groups interested in using the PI platform.

Low digital-literacy levels might be seen as a challenge to the adoption of tools, such as PI. In Latin America, millennials have made the use of tablets and other portable electronics so popular that a great percentage of families, even poor ones, currently have access to the Internet through these devices. Online app managers in our context face a challenge in that many people have limited access to the Internet through Wi-Fi networks. An in-development PI app would store the users' data offline, allowing it to be synchronized once an Internet connection becomes available. This is a great opportunity to increase the scale of this project and reach out to more users.

Moreover, mobility should be considered a key feature of the module. Nowadays, users have frequent access to smartphones. Thus, a future version of the module should include a mobile app; a mobile app could be a game changer in VAA development.

The SA block is only one piece tested in practice as part of the fuzzy profile model proposed in the work of Terán and Kaskina (2016). Nevertheless, the dynamic profile model is not limited to the use of SA. There are still more dynamic elements that can be added to the profile generation that could have a higher accuracy in the recommendations provided by the VAA.

The PI platform still offered more information that can be use in the future as a part of the dynamic profile. For instance, the PI platform included several sections and features to provide information to the users (e.g., discussion forums, statistics, candidate tweets, and personalized RSs).

In terms of the SA block, one can suggest various improvements, such as the consideration of emoticons in the process to identify the sentiment of the tweets and the implementation of a more complete Spanish SA dictionary. Both improvements should be considered in a future version of dynamic profile generation in the VAA module.

Finally, the expectation is that this project will impact citizen decision-making by providing users with relevant information and resources to debate and think about their choices and then make better decisions. This project is expected to impact government actions through informed knowledge and feedback from societies, with the intention of strengthening democracy by using new technologies. Furthermore, the project is expected to extend its use to other contexts and regions within the coming years.

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