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Evaluation of Visualization of a Fuzzy-Based Recommender System for Political Community-Building

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Abstract

Recommender systems are mainly used to reduce information overload and to provide recommendations of products likely to interest a user when given some information about his profile and preferences. The use of recommender systems on *eGovernment* is a research topic that is intended to improve the interaction among public administrations, citizens, and the private sector through reducing information overload on *eGovernment* services. In this work, the evaluation of visualization provided by a fuzzy-based recommender system for stimulating political participation and collaboration is proposed, using different evaluation methods for dimensionality reduction and fuzzy clustering algorithms that are the core of the recommender system approach. The results and recommendations given in this work are used for the implementation of the *SmartParticipation* project for the creation of political/thematic groups, which assumes that profiles of citizens and candidates cannot be considered unique items, but, rather are dynamic.

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Keywords: recommender systems; evaluation; dimensionality reduction; fuzzy clustering; eGovernment; eParticipation

1. Introduction

The need of citizens and other stakeholders for a free democratic debate, and the right to be involved in the decision-making process, is being emphasized by many democratic theorists. The use of Information and Communication Technologies (ICT) has opened new channels for free discussion of political issues, and day by day it is moving away from traditional media like TV, radio, mail, and newspapers. The *SmartParticipation* project, is described in the Ph.D. thesis of Terán [1]. It is a Web-based platform that uses a fuzzy clustering methods for the creation of political/thematic groups, assuming that the profile of citizens and candidates cannot be considered unique items, but, rather is intended dynamic. This is due to the fact that, people's political position might evolve in time. This project uses the database of *smartvote*; a well-known voting advice application (VAA) for local, cantonal, and national elections in Switzerland, conceived as a type of vote recommendation system and intended to provide citizens with a simple and innovative al-

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ternative to enhance participation of citizens in three main areas, *eCollaboration*, *eDemocracy*, and *eCommunity*. This project uses of the definition of Yager [2] about recommender systems (RSs), which makes a distinction between RSs and targeted marketing methods, used for *eCommerce*, by considering RSs as participatory system in which the user intentionally provides information about his preferences. The *SmartParticipation* is based on a fuzzy recommender system (FRS) for political community-building introduced by Terán and Meier [3] and uses a modified fuzzy c-means algorithm (FCM) and the Sammon mapping technique, which is used for visualizing recommendations. This paper is structured as follows: First, Section 2 presents a literature review on RSs and their applications. Section 3 gives a general description of the RS approach and the different visualizations provided. Then, Section 4 gives the evaluation of dimensionality reduction methods. Section 5 presents the validation of clustering methods. A comparison between the visualization provided by the FRS and *smartvote* [4] is presented in Section 6. Finally, concluding remarks, suggestions and the outlook for the implementation of the FRS are presented in Sections 7 and 8.

2. RSs Approaches

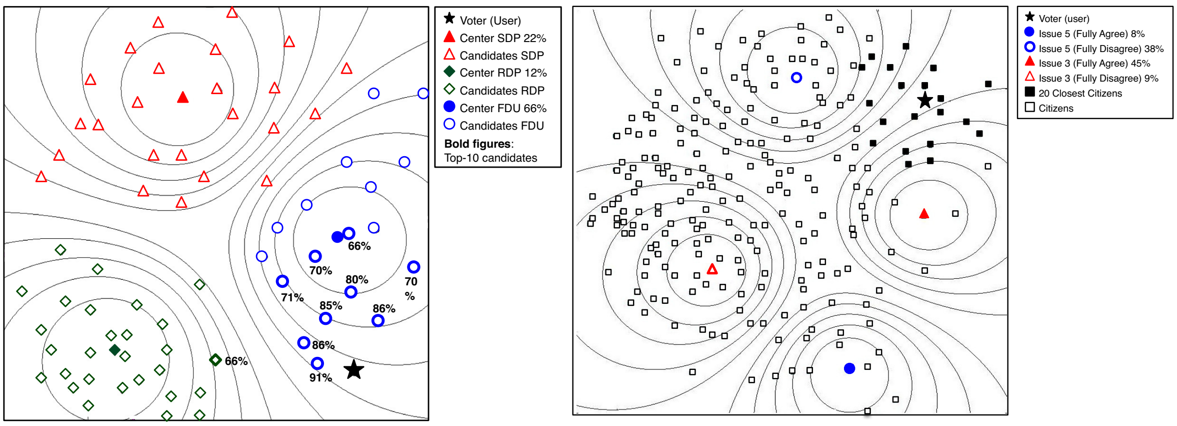
RSs are computer-based techniques that attempt to present information about products that are likely to be of interest to a user. These techniques are mainly used in Electronic Commerce (*eCommerce*) in order to provide suggestions on items that a customer is, presumably, going to like. Nevertheless, there are other applications that make use of RSs, such as social networks and community-building processes. The work of Park et al. [5] provides information about trends in the area of RSs. In this work the authors mention that the first research papers on collaborative filtering were published in the mid-1990s by Resnick et al. [6] and Shardanand and Maes [7]. In their work, Park et al. [5] examine the publication of the articles and provide insight and future direction on RSs using the following databases searching for papers about RSs: ABI/INFORM Database, ACM Portal, EBSCO Academic Search Premier, EBSCO Business Source Premier, IEEE/IEE Library, and Science Direct. Additionally, Park et al. [5] classified the different research papers into two main groups. The first group consists of eight categories by application fields, such as: books, documents, images, movies, music, shopping, TV programs, and others (other fields involve a minority of recommendation fields such as hotels, travel, and food). The second group consists of eight categories by mining techniques, such as: association rule, clustering, decision tree, k-nearest neighbor, link analysis, neural network, regression, and other heuristic methods.

The use of RSs on *eGovernment* is a research area intended to improve the interaction among public administrations, citizens, and the private sector through reducing information overload on *eGovernment* services. Two types of RSs for *eGovernment* were identified and are discussed in the academic literature. The first one corresponds to VAAs, which are online tools that match the preferences of voters with the positions of political parties or candidates. According to Ladner et al. [8], the first operational VAA was the Dutch StemWijzer [9]. It went online for the first time in 1998 and provided 250,000 people with voting advices. In 2006, this figure exploded to 4.7 million voting advices, which represents 40% of the Dutch electorate (Walgrave et al. [10]). The use of VAAs has an important impact on politics and electoral campaigns. In the work of Ladner et al. [8], clear evidence of the increasing popularity of VAAs is shown. The second type of RSs for *eGovernment* are the so-called social voting advice applications (SVAA) that are proposed in the work of Katakis et al. [11]. The authors defined SVAAs to extend VAAs by providing community-based recommendations, comparison of users' political opinions, and a channel of user communication.

The *SmartParticipation* project intends to provide citizens with a simple and innovative alternative using a fuzzy-based RS to enhance participation of citizens in three main areas: *eCollaboration*, *eDemocracy*, and *eCommunity*. The project is based on five participation levels: *eInforming*, *eConsulting*, *eDiscussion*, *eParticipation*, and *eEmpowerment*, which are presented in the work of Terán and Drobnjak [12]. The term *eCollaboration* is also related to collaborative working environments (CWE). The *SmartParticipation* project extends the idea of CWE by taking into account the five participation levels to enhance citizens' participation and to empower citizens in the decision-making process. In the area of *eDemocracy*, *SmartParticipation* extends the idea of VAAs used mainly in *eDiscussion*, providing recommendations with a political landscape of candidate profiles, political parties, and the voters. Finally, on *eCommunity*, the *SmartParticipation* project allows citizens to create and visualize virtual communities based on their profiles, such as new political parties, thematic groups, and civic networks, and participate in national issues by opening channels of discussion and debate through the use of ICTs and Web 2.0.

3. Visualisation of Fuzzy-Based RS

The RS approach was proposed in the work of Terán and Meier [3]. In this work, two types of visualisation are presented. The first one is used for citizenslooking for recommendations of political parties and candidates before an *eElection* process. This type of recommendation is used for the so-called VAAs. Figure 1a displays the formation of clusters with a clear concentration of candidates from the same political party. It shows that the closest political party with respect to the user (represented with a star icon) is the Federal Democratic Union (66%), followed by the Social Democratic Party (22%) and the Radical Democratic Party (12%). This figure uses datasets provided by *smartvote* [4]. The second visualisation is used to create thematic virtual communities, the application of this visualisation is to provide a user (citizen) with recommendation of other users (citizens) that are close to their profiles based on selected issues (discussion topics). Figure 1b shows how close a user is with respect to issues 3 (discussion topic 3) and 5 (discussion topic 5). It shows that the selected user (represented with a star icon) is 45% to the full agreement on issue 3 and 38% to full disagreement on issue 5. The users and issues (topics) are taken from the datasets provided by *smartvote* [4]. The citizens are represented by black squares, and for this experiment the 20 closest citizens are represented by filled black squares. Additional information on the visualisation and recommendation algorithm is available in the work of Terán and Meier [13].



(a) Top-N recommendation for *eElection*

(b) Thematic Communities for *eCommunity*

Figure 1: Visualization of FRS adapted from Terán and Meier [13]

4. Evaluation of Dimensionality Reduction

Dimensionality reduction is being used in different research areas, such as image processing, multivariable data analysis, machine learning, data mining, and RSs, among others. The understanding of high-dimensional data requires the extraction of information from it. The FRS is based on dimensionality reduction to provide users with a visualization of political and thematic landscapes. For this reason, an evaluation of different methods is presented in this section.

4.1. Evaluation Measures

In the academic literature, several measures for evaluating non-linear dimensionality methods have been proposed. In this section, a methodology presented in the work of Venna and Kaski [14,15] is used to evaluate five dimensionality reduction algorithms. It considers two measures: “trustworthiness” and “continuity.”

4.2. Dimensionality Reduction Methods

The FRS proposed in this paper makes use of dimensionality reduction to better understand the inter-distance relations in a recommendation. A non-exhaustive analysis of dimensionality reduction methods is presented in this section. Five dimensionality reduction methods are analyzed and compared: (1) Principal Component Analysis (PCA) by Pearson [16], (2) Sammon mapping by Sammon [17], (3) t-Distributed Stochastic Neighbor Embedding (t-SNE) by van der Maaten and Hinton [18], (4) Isomap by Tenenbaum et al. [19], and (5) Locally Linear Embedding (LLE) by Roweis and Saul [20]. To visualize the results provided by each fuzzy clustering method, two datasets provided by the *smartvote* [4] project are used.

4.3. Evaluation of Results

The section presents the evaluation of the five dimensionality reduction methods described in the previous section. Before presenting the results of the evaluation, it is important to describe the setup of the experiments for each algorithm. Table 1 summarizes the different parameters used for the evaluation. The results of the evaluation are presented in Fig. 3 and use the datasets provided by the *smartvote* [4] project. To better understand the results presented, the analysis has been divided into two datasets, one with three political parties and the second with 15 political parties.

Table 1: Parameters used for the evaluation

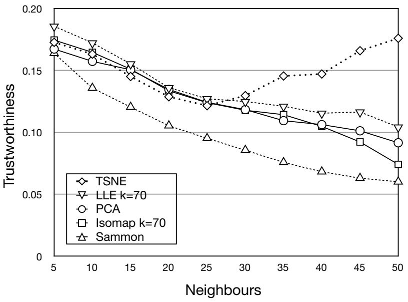
Method	**Parameters**
PCA	none
Sammon	Initialization: PCA, max iterations: 1000, $\epsilon = 1e^{-10}$
t-SNE	Initialization: PCA, perplexity: 30
LLE	Dataset with 3 Political Parties, $k = 60$. Dataset with 15 Political Parties, $k = 60$
Isomap	Dataset with 3 Political Parties, $k = 60$. Dataset with 15 Political Parties, $k = 60$

Dataset with three political parties. Figs. 2a and 2b present the evaluation of trustworthiness and continuity using a dataset with three political parties. In the case of trustworthiness, the performance of all the algorithms is similar for a small number of neighbors (five neighbors). Nevertheless, for the higher number of neighbors, there is a considerable improvement of approximately 11.5% with respect to the best (t-SNE) and worst (Sammon) cases. For the case of continuity, there is a clear improvement of performance for the best (t-SNE) and worst (Sammon) cases while increasing the number of neighbors. The performance increased from approximately 5% (five neighbors) to approximately 12.7% (50 neighbors).

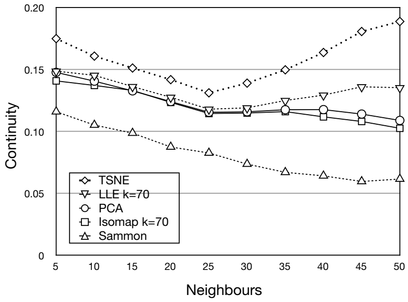
Dataset with 15 political parties. Figs. 2c and 2d present the evaluation of trustworthiness and continuity using a dataset with fifteen political parties. The results show that, for both trustworthiness and continuity, there is a clear improvement with the best (LLE) and worst (PCA) cases while increasing the number of neighbors. The performance increased from approximately 9% (five neighbors) to approximately 7.3% (50 neighbors) in the case of trustworthiness, and from approximately 10.6% (five neighbors) to approximately 8.6% (50 neighbors) in the case of continuity.

4.4. Analysis of Results

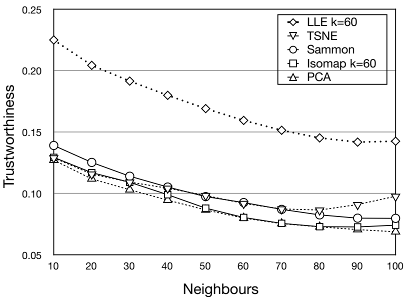
In the previous section, a non-exhaustive quantitative evaluation of dimensionality reduction methods is presented. Nevertheless, selecting the algorithm does not depend only on the performance but also on the number of parameters to be adjusted. It is important to mention that different algorithms have different performances depending on the dataset, number of dimensions, and number of data points. In the work of Van der Maaten et al. [21], twelve techniques were tested with artificial and natural datasets. The authors showed that, for artificial datasets, techniques based on neighborhood graphs such as Isomap, MVU, LLE, Laplacian Eigenmaps, LTSA, and Hessian LLE presented better performances. The techniques that do not employ neighborhood graphs such as PCA, Sammon mapping, and autoencoders, presented better performances. In the case of the FRS, presented in this work, the selection of the



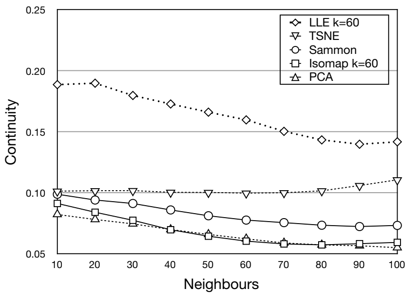
(a) Trustworthiness - 3 Pol. Part.



(b) Continuity - 3 Pol. Part.



(c) Trustworthiness - 15 Pol. Part.



(d) Continuity - 15 Pol. Part.

Figure 2: Evaluation of five dimensionality reduction methods

Table 2: Properties of Techniques for Dimensionality Reduction. Adapted from Van der Maaten et al.[21]

Method	Parameters	Computational	Memory
PCA	none	$O(D^3)$	$O(D^2)$
Sammon	none	$O(in^2)$	$O(n^2)$
t-SNE	perplexity: *perp*	$O(n^2)$	$O(n^2)$
LLE	neighbors: k	$O(pn^2)$	$O(pn^2)$
Isomap	neighbors: k	$O(n^3)$	$O(n^2)$

dimensionality reduction method considers two factors: complexity and computational/memory performance. Table 2 summarizes the three main properties of each algorithm evaluated.

PCA and Sammon techniques can both be considered non-parametric. The other methods studied can be considered parametric, and their performance depends on the selection of these parameters. In the case of t-SNE, for different executions of the algorithm that produce different outputs, the interpretation is that they can fall in a local optimum (a solution that is not exactly the best), but only an approximation. They often require a careful adjustment of several hyperparameters (e.g., k neighbors) to fasten the convergence and avoid the local minima and converge to a global minima. Taking into account that the FRS works using Euclidean distances for simplicity proposes, the FRS uses the Sammon mapping technique in order to provide the visualization of dimensionality reduction. Additionally, to guarantee the presence of a local optimum, an initialization with the PCA is used.

5. Validation of Fuzzy Clustering

Balasko et al.[22] refer to fuzzy cluster validation as the problem of whether a given fuzzy partition fits a given data point. Different fuzzy clustering methods are proposed in academic literature, aiming to find the best fit for a fixed number of clusters and cluster shapes. The results provided by different fuzzy clustering methods depend on the number of clusters, the initialization method, and cluster shapes. For that reason, different validation methods, which are proposed in the academic literature, are presented in this section. These methods are used to perform a non-exhaustive validation of fuzzy clustering methods.

Seven methods are used for validation of clustering methods, which are: (1) Partition Coefficient (PC) by Bezdek [23], (2) Classification Entropy (CE), (3) Partition Index (SC) by Bensaid et al. [24], (4) Separation Index (S) by Bensaid et al. [24], (5) Xie and Beni's Index (XB) by Xie and Beni [25], (6) Dunn's Index (DI) by Dunn [26], and (7) Alternative Dunn's Index (ADI).

The FRS in this paper uses fuzzy clustering to provide recommendations. It defines the center of clusters as a reference for both political parties and issues in a bi-dimensional landscape. In this section, three methods are analyzed and compared: (1) Fuzzy C-means Algorithm (FCM) by Pearson [16], (2) Fuzzy Gustafson-Kessel Algorithm (FGK) by Gustafson and Kessel [27], and (3) Fuzzy Gath-Geva Algorithm (FGG) by Bezdek and Dunn [28]. To visualize the results provided by each fuzzy clustering method, two datasets provided by the *smartvote* [4] project are used. The first dataset corresponds to candidates of three political parties (80 candidates in total), and the second dataset corresponds to the candidates of 15 political parties (213 candidates in total). Both datasets are composed of profiles with 73 dimensions (questions).

5.1. Evaluation of Results

In this section, the validation of the three fuzzy clustering methods described previously is performed using the methods presented in previously. To better understand the results presented, the analysis is divided two parts, the fist one with three political parties and the second with 13 political parties.

Dataset with three political parties. Table 3 presents the validation with the methods described in Section 5 and uses a dataset of *smartvote* [4] with three political parties. The results show that the FCM algorithm has a better performance using the validation methods CE and DI. The FGG algorithm shows better performance when using the validation methods SC and S. Finally, the FGG algorithm shows better performance when using the validation methods PC, XB, and ADI. The values shown in bold represent the highest performance.

Table 3: Validation of Fuzzy Cluster Methods - 3 Political Parties

Method	PC[1]	CE[2]	SC[3]	S[4]	XB[5]	DI[6]	ADI[6]
FCM	0.7069	**0.5372**	1.1041	0.0160	4.2152	**0.1327**	0.0014
FGK	0.7455	0.35719	**1.0416**	**0.0154**	3.5832	0.0905	0.0051
FGG	**0.9614**	0.0707	2.1258	0.0311	**1.6861**	0.0202	**0.1118**

[1] Highest value represents a highest overlapping between clusters.
[2] Highest value represents a highest level of fuzziness.
[3] Lowest value represents a better partition.
[4] Lowest value represents a highest separation between clusters.
[5] Lowest value represents a highest level of compactness and well separated clusters.
[6] Highest value represents a highest level of compactness and well separated clusters.

Dataset with fifteen political parties. Table 4 presents the validation with the methods described in Section 5 and uses a dataset of *smartvote* [4] with 13 political parties. The first observation that has to made is that the performance of different validation methods decreases when the number of clusters increases. The results presented in Table 4 show that the FCM algorithm has a better performance with the validation methods CE, SC, XB, and DI. The FGK algorithm presented a better performance when using the validation method S. Finally, the FGG algorithm performed better using the validation methods PC and ADI. The values shown in bold represent the highest performance.

Table 4 shows that FGG presents NaN values when using CE, SC, S, and XB. This can be explained due to the hardly detectable connection to the data structure and the high level of overlapping of cluster centers when using the FGG algorithm. In the work of Balasko et al. [22], the authors mention that the most useful validation methods when comparing different clustering algorithms are SC and S with the same value of c.

Table 4: Validation of Fuzzy Cluster Methods - 15 Political Parties

Method	PC[1]	CE[2]	SC[3]	S[4]	XB[5]	DI[6]	ADI[6]
FCM	0.35287	**1.4122**	**0.7680**	0.0064	**1.8545**	**0.0652**	0.0004
FGK	0.35703	1.2803	0.7795	**0.0059**	2.3409	0.0521	0.0015
FGG	**0.8504**	NaN[7]	NaN[7]	NaN[7]	NaN[7]	0.0514	**0.0438**

[1] Highest value represents a highest overlapping between clusters.
[2] Highest value represents a highest level of fuzziness.
[3] Lowest value represents a better partition.
[4] Lowest value represents a highest separation between clusters.
[5] Lowest value represents a highest level of compactness and well separated clusters.
[6] Highest value represents a highest level of compactness and well separated clusters.
[7] Not a number.

5.2. Analysis of Results

In the previous section, a non-exhaustive quantitative evaluation of fuzzy clustering methods is presented. Nevertheless, making a selection of the algorithm does not depend only on the performance but also on the number of parameters to be adjusted. It is important to mention that different algorithms have different performances depending on the structure of the dataset and the number of clusters. In their work, Balasko et al.[22], mentioned that besides of having different methods for the validation of fuzzy clustering, none of these methods can be considered as perfect. Based on the results presented in previous sections, some conclusions can be made. Firstly, the FCM algorithm has a good performance and a lower complexity compared to the FGK and FGG algorithms. Both the FCM and FGK algorithms are more suitable for spherical clusters and the FGK algorithm is more suitable for linear clusters. Secondly, the FGK algorithm presents an advantage compared to the FCM algorithm since each cluster has the property to adapt the distance norm to the local topological structure. A disadvantages of this algorithm, is that, it requires a priori knowledge of ρ for each cluster. In the examples shown in previous sections, a constant value of $\rho = 1$ was used, so the algorithm finds clusters with approximately equal volume. Finally, the FGG algorithm has shown better performance in terms of validation in the case of small numbers of clusters. Nevertheless, it can be compared to c-means algorithm.

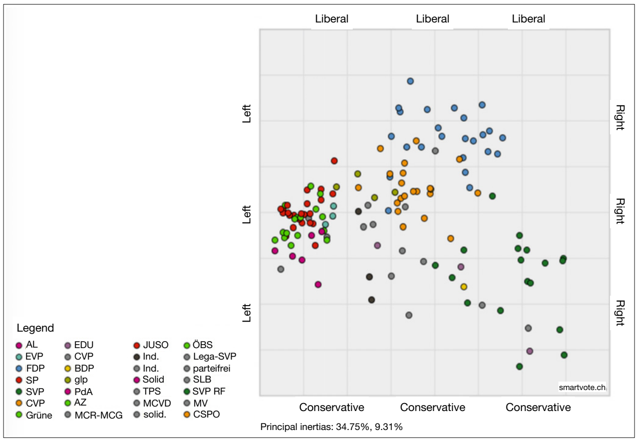
For the reasons mentioned above, the author recommends the use of the FCM and the FGK for the implementation of the RS approach proposed in this paper, which uses the datasets provided by the *smartvote* project. It is important to mention that the results provided by different algorithms directly depend on the datasets selected, the number of clusters, and the particular shapes of the clusters, among other reasons.

6. Comparison with *smartvote*

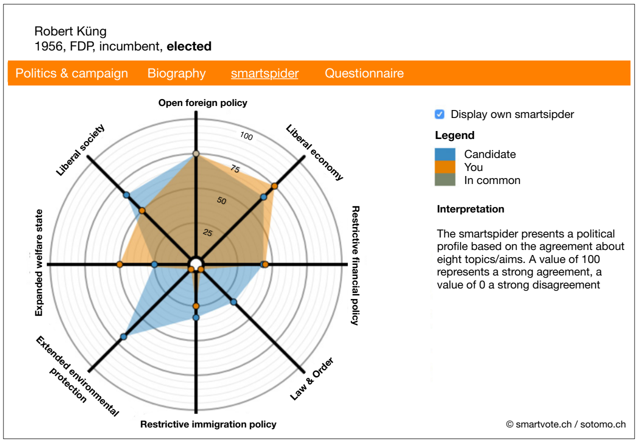
The *smartvote* project is a VAA that provides recommendations before an *eElection* or *eVoting* process. It provides with visualization for political profiles which are described ad follows:

- The *smartmap* shows political positions in a two-dimensional coordinate system, where the north-south axis represents a liberal-conservative tendency, and the west-east axis represents a left-right tendency. Figure 3a shows an example of *smartmap*. More details about this visualisation are available at[29].
- The *smartspider* expresses the strength of attitudes and positions of political candidates based on themes. The smartspider has eight axes that are oriented from the perspective of their content to areas of Swiss politics. Figure 3b shows an example of a *smartspider* that indicates the political tendencies of a specific candidate and the voter. More details about this visualisation are available at[30].
- Additionally, *smartvote* offers a comprehensive database of all candidates that consists of a political profile, information about their political careers and agendas, details about their education, professional and family backgrounds, as well as links to their personal websites, video and audio interviews.

The main differences between the recommender system proposed and the *smartvote* project are the computation of similarities and the way recommendations are displayed to users. *smartvote* computes similarities based on “match



(a) *smartmap* visualization



(b) *smartspider* visualization

Figure 3: Main visualizations from *smartvote* [4]

point" as described in [31]. The recommendations are displayed as a list of the closest candidates with a percentage of similarity. The FRS computes similarities based on distances in a high-dimensional space. In addition, it computes fuzzy clusters based on the number of political parties which are part of an *eElection* process, where candidates and voters described in a finest granularity can belong to several clusters. The recommendations in the FRS are displayed in a bi-dimensional political landscape, which includes the percentage of similarity of the Top-N closest candidates (see Figure 1a). Therefore, relationships to closest "neighbors" can be derived and analyzed.

Additionally, the FRS provides a visualisation that can be used to create thematic communities (see Figure 1b). User can define their profiles and the system will generate a thematic landscape, allowing a user to identify other users with similar preferences. This visualisation can be also used to identify totally different points of view. This type of recommendation can be used to organise debates, where, it is important to identifying users with opposite arguments. In this scenario, the recommendation of totally opposite positions could be useful. The community creation could be used also in the case of *eCollaboration*, where both: public and private sector, are looking for interesting profiles in a collaborative working environment.

The creation of political communities allows 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 the information and knowledge-based society.

7. Conclusions

In this paper, the evaluation of visualisation of a RS for political community-building is presented. The recommendation engine can be used to visualize differentiated clusters of politicians as well as of citizens. It, therefore, supports collaboration, voting advice, building processes for political communities that share common objectives, and civic participation. The core of the FRS evaluated in this work is based on dimensionality reduction and a fuzzy clustering approach, it computes similarities between citizens and politicians in a multi-dimensional space.

In this work, the use of Sammon mapping techniques for dimensionality reduction, as well as FCM and the FGK for clustering, is recommended for the implementation of *SmartParticipation*. The RS approach presented in this work differs from collaborative filtering methods in that the latter are based on past experiences. It is also suitable in the one-and-only scenario, in which events such as election processes occur only once, and their participants (candidates and/or citizens) cannot be considered unique, since their presence at such events and their way of thinking can vary over time.

The use of RSs on *eGovernment* is a research area that is rapidly growing and is intended to improve the interaction among public administrations, citizens, and the private sector through reducing information overload on *eGovernment* services. The visualization proposed by the FRS for *SmartParticipation* allows for a better understanding and evaluation of the recommendations and relationships among citizens and/or politicians, thematic groups, etc, using a bi-dimensional graphical interface.

The *SmartParticipation* project intends to provide users with a simple and innovative alternative using a fuzzy-based RS to enhance participation of users in three main areas, *eCollaboration*, *eDemocracy*, and *eCommunity*, to allow citizens to create and visualize virtual communities based on their profiles, such as new political parties, thematic groups, and civic networks, and participate in national issues by opening channels of discussion and debate through the use of ICTs and Web 2.0. The *SmartParticipation* project is not intended to compete with other VAA projects, but rather complement its features and functionalities.

8. Outlook

RSs can be considered a multidisciplinary research topic that includes a wide range of areas, such as machine learning, data mining, information retrieval, human computer interaction, and data visualization, among others. In addition to the various solutions presented in this paper, many ideas have been proposed and other questions remain open. The inclusion of sentiment analysis (or opinion mining) to enhance the dynamic profile generation. Context-Awareness in recommendation including contextual information could used to improve the prediction accuracy of RSs. Future work can include additional functionalities to support context-awareness for the *SmartParticipation* project.

The *SmartParticipaton* platform is intended to reach the highest level of participation, the so-called *eEmpowerment*, presented in the work of Terán and Drobnjak [12], which places the final decision in the hands of the citizens. In addition to traditional crisp voting systems, an alternative, fuzzy-based, method could be tested.

Besides all the features proposed by the *SmartParticipation* project, future work could include additional tools for improving political controlling. An example of this can be the analysis of voting from elected authorities. Their profiles can be analyzed before and after an election process using the answers provided to the system and the dynamic profile, which can give additional information for the analysis. Political programs can also be analyzed, including an evaluation of their performance.

Finally, to better understand the difference between the recommendations provided by *smarvote* and the FRS, an in depth study should be conducted including, advantages, disadvantages, and error metrics, among others.

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