Adaptive Visualization of Social Media Data for Policy Modeling

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Abstract. The visual analysis of social media data emerged a huge number of interactive visual representations that use different characteristics of the data to enable the process of information acquisition. The social data are used in the domain of policy modeling to gather information about citizens' demands, opinions, and requirements and help to decide about political policies. Although existing systems already provide a huge number of visual analysis tools, the search and exploration paradigm is not really clear. Furthermore, the systems commonly do not provide any kind of human centered adaptation for the different stakeholders involved in the policy making process. In this paper, we introduce a novel approach that investigates the exploration and search paradigm from two different perspectives and enables a visual adaptation to support the exploration and analysis process.

1 Introduction

The involvement of citizens opinions and discussions of citizens in the policy creation process plays an increasing role. The Web provides vast amounts of social data, which can be used to identify problems and consider citizens' opinions in the policy creation process. The masses of information are difficult to handle. Everyday new opinions, discussions etc. and thereby new data are available [1]. The process of policy modeling is characterized among others by making decisions [2–4]. This process involves stakeholders, who may have different roles and thereby vary in their prior-knowledge, preferences, or way of work. The range of differing users starts with citizens, who are involved passively in the process of policy creation over analysts with deeper understanding of given policy and political problems to real politicians, who scarcely make use of analysis or visualization tools for their decision. Although there exist a great number of visualizations that investigate the formalized knowledge representation as given in social media [5–8]. Commonly the heterogeneity of stakeholders are not considered in those systems. Typically, the social relations are visualized as graph-based networks that allow to gather relationships of actors or media and the statistical value is commonly visualized in a temporal manner that illustrates the temporal

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spread of certain topics or moods. The most important factor in context of social media analysis is the human access to the daily increasing amount of data. Information visualization is a promising discipline facing the information-access challenge by investigating the areas of human perception, human-computer interaction, data-mining, and computer vision [2,3]. Information visualization and visual analytics enable the acquisition of knowledge from the underlying data and provide insights [9]. The human access to data is provided by interactive pictures of knowledge and enables solving various knowledge and information related policy tasks. These pictures are generated through transformation and mapping of data [10] to visual variables [11] that are perceived by human to solve tasks [12]. Two complimentary approaches in search and human information retrieval enable gathering and analyzing information to enable a more efficient decision support. Firstly, the renown *Information Seeking Mantra* that proposed to get first an overview of the entire domain knowledge in an abstracted way, followed by zooming and details on demand to get more information about the knowledge-of-interest [12]. This top-down approach makes use of our natural interaction with the real world. Getting into a new situation forces us to build association of known or similar situations [2]. Secondly, the more conventional search process that proposes a bottom-up approach and premises the verbalization ability for a more goal directed problem solving [13, 14]. The visual representation is then generated from the results of a search query. In the context of information visualization the aspects of data, user and tasks are of great importance [3]. For designing Information Visualization tools the question, "'which data to what kind of users and for solving which tasks may provide an adequate design process?"' In this context, the recent research investigates in particular the feedback loop to the data in Visual Analytics, the model-based visual knowledge representation in Semantics Visualization and the cognitive-complexity reduction of users in Adaptive Information Visualizations (AIV) [2].

In this paper, we introduce an approach that makes use of adaptive visualizations for supporting the top-down and bottom-up search approach of social media data. The social media data are formalized as a light-weight ontology by text-mining methods [15], and provide a structured and semantically enriched access to the data [16]. This paper aims not at giving an insight of how the data are processes or topics are generated, it focuses more on the part of visual adaptation based on the overall search and interaction process in particular for policy modeling.

2 Related Work

The visual analysis of social media data emerged a huge number of interactive visual representations that use different characteristics of the data to enable the process of information acquisition. Wang et al. introduced with their *LeadLine* an interactive visual system that visualizes topics, persons, locations and point of data by extracting events from social media data by text-processing methods [17]. The interaction process is more top-down with the used color-coded bursts and supports the illustration of related events [17]. Situation awareness is targeted and supported by *SensePlace2* proposed by MacEacheron et al. [18]. They propose a visual search and monitoring interface with multiple windows for geolocated Twitter monitoring. Their approach is more bottom-up, thus the search starts with a search-term and visualizes the contextual spread in a more geolocated manner. The system is not considering any adaptation criteria on data or user. Shi et al. introduced with *HiMap* an approach for visualizing masses of social network connection in a hierarchical and comprehensible manner [19]. They introduce their approach based on a pipeline with three main steps, *Offline Data Manipulation*, *Adaptive Data Loading/Summarization*, and *Clustered Graph Visualization*. They make use of a single force-directed algorithm [20] for visualizing the nodes and links of the social networks. Their enhanced graph-layout algorithm limits the visualized levels of cluster-hierarchy to not overload the user with information. To compensate this limitation, two enhanced zooming abilities are included beside a *geometric zoom*, *hierarchical zoom* and *semantic zoom*. *HiMap* provides an interesting approach for a comprehensible view on complex network data. It integrates a kind of adaptive feature for loading data that incorporates various aspects and reduces or expands the amount of visualized entities. However, the reduction and expansion of loaded data is the only adaptive functionality. Further, the user and the relevance based on any user characteristics is not considered at all. Dork et al. introduced a "visual backchannel" [21] that visualizes text, attached images, and authors' identities from social media data. Their approach enables a top-down exploration and monitoring of emerging topics. They use a stacked graph for the temporal spread of topics and terms, a spiral visualization for participants and their activities, and an image cloud for pictures [21]. Although their system investigates a number of various information that are presented in juxtaposed manner on the screen, the visual representation is always the same. There are no adaptations, or changes in search metaphor.

Our short review on related work illustrates that commonly the top-down search paradigm is used for visualizing social media data, even for different roles and stakeholders. Adaptive visualizations that support both, a top-down and bottom-up search are not proposed to our knowledge. Some adaptive features seems to be necessary, if the process of policy modeling is investigated.

3 Policy Modeling Steps

Policies are usually defined as principles and statements that assist decision-making and guide political processes. One aspect of process-driven policy making is the clear definition of the sequence of steps in the policy creation process. This ensures the consideration of the most relevant issues that might affect a policys quality, which is directly linked to its effectiveness. Macintosh proposed a policy-making life cycle that comprises the steps of *Agenda Setting*, *Analysis*, *Policy Creation*, *Policy Implementation*, and *Policy Monitoring* [22]. Agenda setting defines the need for a policy or a change to an existing policy and clarifies the problem that triggered the policy need or change. Analysis clarifies the challenges and opportunities in relation to the agenda. This steps goals are examining the evidence, gathering knowledge, and a variety of options. Policy creation aims to create a good workable policy document, taking into consideration a variety of mechanisms such as risk analysis or pilot studies. Policy implementation can involve the development of legislation, regulation, and so on. Policy monitoring might involve evaluation and review of the policy in action [2, 22].

The general process model of Macintosh was applied to identify the need and advances of information visualization in context of social media data [3]. Therefore the model was abstracted for identifying general and abstract information visualization steps: The need for a policy, the policy design, and impacts of the designed policy

For adopting visualizations in policy making, we simplified the general model and introduced three iterative stages [2, 3]: (1) *Information Foraging* supports policy definition. This stage requires visualization techniques that obtain relations between aspects, statistical information and policy-related issues. Such visualized information enables analyzing the need for a policy. (2) *Policy Design* visualizes the correlation between topics and policy requirements to ensure a new or a revised functional interoperability of a policy and (3) *Impact Analysis* evaluates the potential or actual impact and performance of a designed policy, which must be adequately visualized to support the further policy improvement [2, 3].

All phases involve heterogeneous data sources to allow the analysis of various viewpoints, opinions, and possibilities. Without visualizations and interactive interfaces, handling of and access to such data is usually complex and overwhelming. The key is to provide information in a topic-related, problem-specific way that lets policy makers better understand the problem and alternative solutions. The gap between information need and information access can be efficiently closed via information visualization techniques.

4 Search and Exploration Paradigms: Top-Down and Bottom-Up Visual Search

Exploratory search enables with the different stages of exploration the acquisition of in particular implicit knowledge or information. Implicit in this context refers to the kind of knowledge or information that is not explicitly known or may not be formulated by the user explicitly, due the lack of knowledge. From the visualization point of view, implicit knowledge or information refer to the knowledge that is not explicitly modeled in the data but can be enlightened through the visualization of the modeled data [13].

Different disciplines provide technologies, systems, and approaches to enable the acquisition of implicit knowledge or information. For simplifying the investigation of these approaches, we classify the methods into *bottom-up* and *top-down* approaches. The standard search process [23], e.g. is a simplification of a bottom-up approach. The approach attempts to formalize the iterative search process, a three-stepped model of *Query Formulation*, *Query Refinement* and *Result Processing*. This model assumes that the search begins with the formulation of query of known knowledge. During the search process the subject gets more knowledge about a certain topic to refine his query, which allows the gathering of additional knowledge about the certain topic. The main aspect of this model is that the search process starts with the ability to formulate a query and to reformulate the query during the search. During the search process new knowledge is adopted, which leads to a reformulation of the query. A more complex example for a bottom-up information gathering and search process is the *information-seeking process Marchionini* [24]. This process includes eight phases and encloses the internalized problem solving of subjects too. *Marchionini*'s model consists of eight phases in information seeking: *Recognize and accept an information problem*, *Define and understand the problem*, *Choose a search system*, *Formulate a query*, *Execute search*, *Examine results*, *Extract information and Reflect/iterate/stop* [24, pp. 49-58], [13].

The exploratory search approaches are per se bottom-up approaches that start commonly with a search term and enable in different stages the investigation, reformulation, learning, and refining. The process of information exploration in information visualization is contrary to the bottom-up approaches of search interface. Commonly in this context a top-down approach is proposed [12], e.g. the *Visual Information Seeking Mantra* [12]. This model proposes the opposite of the bottom-up approach and is designed for visual information seeking. The three-stepped model propagates to overview the data first, then zoom and filter the relevant parts and finally gather details on demand. Beginning with the overview of data, this model does not premise the verbalization ability, here the focus is on the recognition ability. If a subject detects in the overview step an area-of-interest, he can zoom into the area or filter this information out. After he gets enough information to recognize a seeking problem, details about the information can be fetched. The top-down model of search and information acquisition based on Shneiderman's work is applied to many visualization environments and is the main approach for gathering information in visual environments [13]. The investigation of the search process in a bottom-up manner plays an increasing role in visualizations. van Ham and Perer for instance proposed a bottom-up search approach in visual environments [14] that starts with *search*, by means of querying the data-set followed by *show context* that enables the contextual view on data and *expand on demand* that provides a detailed view on demand (see Figure 1).

The described seeking approaches require different human abilities for solving a seeking problem. In a bottom-up approach the formulation of the searched topic is important, whereas the recognition ability plays an important role in the top-down approaches. The mentioned top-down approaches are primarily information visualization approaches, thus the overview of information and recognition of area-of-interest can be more supported with visualization systems.

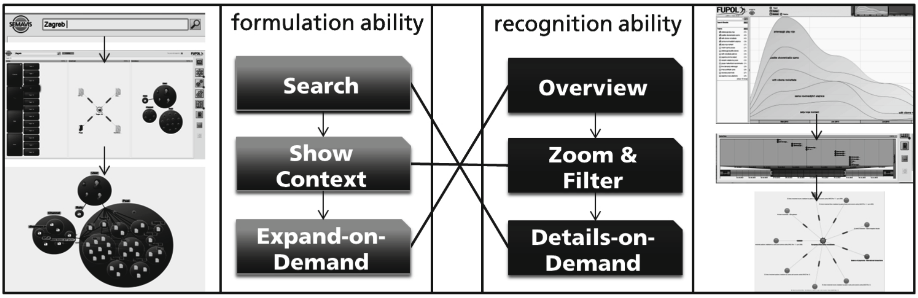

Fig. 1. Visual Exploration: Bottom-up [14] and Top-down [12] with tentative examples

5 Visualizing Social Media Data

Our visualization approach makes use of formalized social media data that is crawled [16], extracted via text-mining methods [15] to generate topics, and formalized to an ontology that consists partially from SIOC and FOAF [25]. Although the ontology provides a formalized and accessible way of the masses of social data, the problem still remains that only a low hierarchy is provided with masses on instances in each concept, e.g. the class "Topic" may contain a large number of topics. This is in particular a challenge for web-based visualizations. To face this problem, we applied the bottom-up and top-search paradigm for accessing the social media data. Overall, the approach applies four different *views* on data:

- Overview visualization of the ontology as a temporal, geographical and/or categorical spread
- Details-on-Demand visualization on graph-based structures
- Combined visualization of the Overview+Detail in a multi-visualization user interface
- Use of the described visualization primitives in the various levels of visual representation

The overview visualization is performed with three different views on data: temporal spread, categorical overview, and geographical overview. One way of visualizing an overview of the whole spectrum of information is the consideration of the temporal attributes. We propose that the temporal view is the most beneficial way to view the trend of upcoming social opinions. Further, interacting with and filtering semantic data for topic-of-relevance based on time may lead to a reduction of information. Here we propose the use of a stacked graph with the using the following visual variables: *Size* for quantity of topics or extracted features, *color* for relevance based on the computed relevance, and the X-Axis for temporal spread. Beside the temporal overview, the thematic arrangement enables a visual overview definition of "categories-of-interest", whereas the information is visualized interactively. We apply in this context two main visualization types to visualize the computed relevance and the result of a quantitative analysis on the user request. The different informational requirements are then visualized on the presentation level by using the visual variables [26]. The size of a graphical entity provides quantitative information whereas the relevance is visualized by color. The overview aspect can be investigated from the geographical point of view too. This visual representation here investigates the geographical spread. This visualization is beneficial when the data can be assigned to geographical attributes and the temporal space is set to a specific value, e.g. todays topics-of-relevance in Barnsley. The quantitative value cannot be considered in this view. It visualizes the geographical spread of topics on a map. The color indicates the topic related to a hot-area and this area can be named by the identified topics.

The next step after the overview is a more detailed view with relational information. Therefore the existing graph-based visualizations will be extended to visualize the dependencies between actors and topics, between actors themselves and between topics themselves. This step can be done after a refinement on the overview visualization or based on a specific search that contains a comprehensible number of entities. In all the steps we have defined different visualization types that are appropriate to meet the informational requirements from the social data part of view. One of the main contributions is that the visual change of the steps from overview to details and vice versa is recognized automatically and appropriate visualizations are provided in combined user interfaces.

Thus, it is not always obvious which term or topic is of interest for citizens in context of their environment, city or country. A bottom-up search would does not always lead to efficient results or provide a view on emerging or interesting topics to be considered in the policy modeling process. To face this problem, we apply top-down search for gathering knowledge in problem identification on social level etc. The top-down approach integrates the introduced search interface as well as a temporal overview of topics. The temporal overview provides a kind of faceting the search space to reduce the information amount on relevant aspects. On the

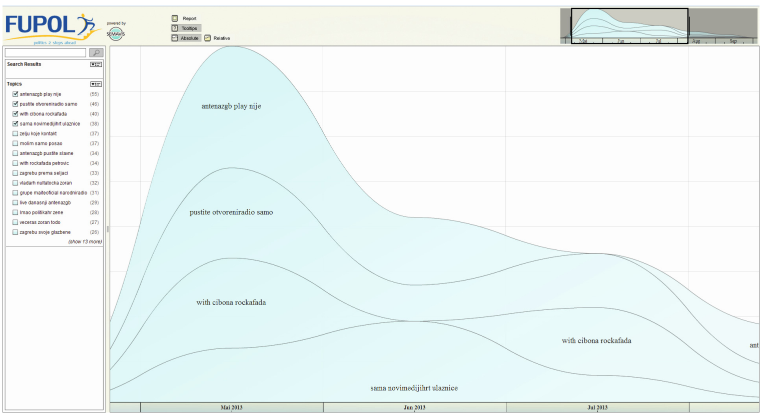

Fig. 2. Temporal overview of political topics

visualization level "details-on-demand" and graph-based visualizations provide a comprehensible view on the information relationships. With the integrated visual layouts of SemaVis, the level of detail may reveal fine granular or textual information. Thereby we follow the visual information seeking mantra proposed by Shneiderman [12]. Figure 2 illustrates the temporal overview with the temporal spread of the topics. The topics are chosen from the left bar, in which a list illustrates all emerging topics. Topics of interest can be selected to view their temporal spread. The visualized data are extracted terms from Croatian social media resources.

6 Visual Adaptation

The temporal overview on extracted topics is kept simple. It is not combined with the visual interface to provide a clear and comprehensible picture of the topics' evolutions. Only the temporal view is placed to provide such an overview. This view on the data is not adaptive. Although the selection interactions of users are stored in a canonical user model [27], an adaptation is not provided due to the simple way of visualization. However the simple overview on data enables the user to choose one of the visualized topics to get detailed information about the topic. After a user has chosen a topic of interest, he gets with a double click detailed information. In particular the *channel* that refers to the source of the topic, the *actors* that refer to the persons or institutions that published their position, and *post* that include the text that was published, is visualized with their semantic relations. In this application scenario the adaptation is limited to the visual layouts and their composition on screen based on the canonical user model and the data amount. Commonly the size of icons or graphical representations of data refer to the amount of related or included postings. The average usage of the visual layouts and their placements are stored to enable an adequate view on the underlying data. Thus in this context commonly the topic, channel, or actor with the most postings is of interest for the policy makers, the visual variables only refers to the amount of relations and postings. Figure 3 illustrates the canonical adapted visual interface after the choice of a topic in the overview visualization. Thereby four visual layouts give detailed information about the chosen topic. We can see at a glance that all postings about the chosen topic were published via Twitter, due to its iconic logo. Further one actor seems to post more about the certain topic, due to the greater size of the icon. The temporal visual layout illustrates the amount of topics in a more detailed way. The figure illustrates the topic postings on a daily interval.

The adaptation of visualization refers in this case to a canonical user model that represents the average usage behavior of all users or users of a certain group, e.g. stakeholders [28] and the amount and structure of the underlying data. The adaptation engine adapts the visual layout and their composition. The visual variables are dedicated for relevance measures of the extracted topics that provide a kind of weighting based on the various factors, e.g. amount of previous postings or relation to other relevant persons. Thereby only the size as visual variable is used. The interactions of users are enhancing the canonical

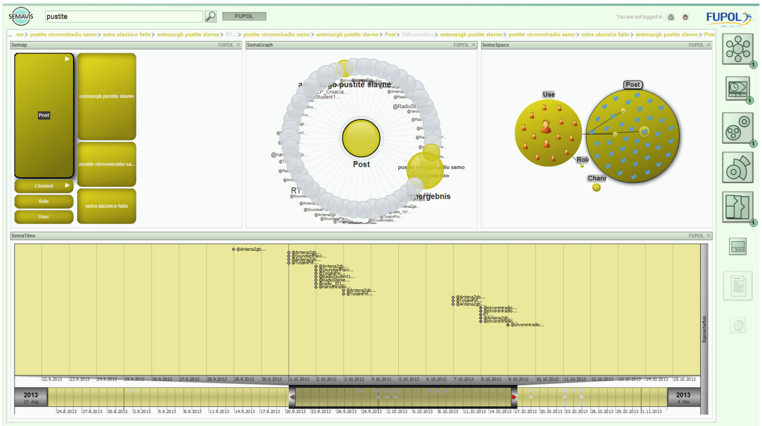

Fig. 3. Detailed view on a chosen topic

user model and based on this the entire system behavior changes. However, the visual variables are not used for the canonical user model; the user is still able to login as individual. Thereby the individual user model of the certain user is applied to adapt the visual appearance. Figure 4 illustrates a view on the data of another topic, which includes news articles. Thereby the user is logged-in as individual. The composition of the visual layouts, the choice of visual layouts, and the visual variables are adapted to the individual user model.

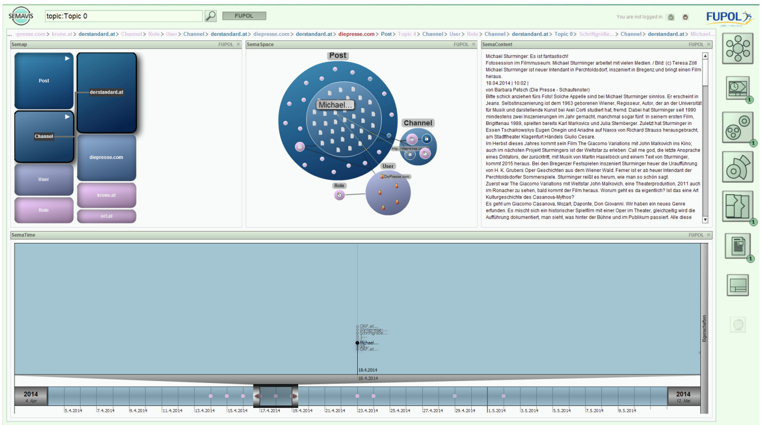

Fig. 4. Adaptation based on individual user model

The work on this application scenario is still ongoing. During the investigation, we identified different roles in the modeling process of policies that should be considered in the adaptation process. Further we identified the necessity of simple one-dimensional visual layouts for quantitative data, thus the social opinions and their relationships would just fulfill a small part of the full set of requirements. Although, an enhanced version (see Figure 5) [29] was applied for statistical data-bases, e.g. *Eurostat*, the requirements of the stakeholder goes beyond this data and visual layouts. The users in the domain of policy modeling differ in their prior knowledge, interests, and intentions. But the main aspect is that they have further different political perspectives on the same issue. The goal should be to provide a more goal-oriented view on the facts and apply for instance process-oriented adaptation methods.

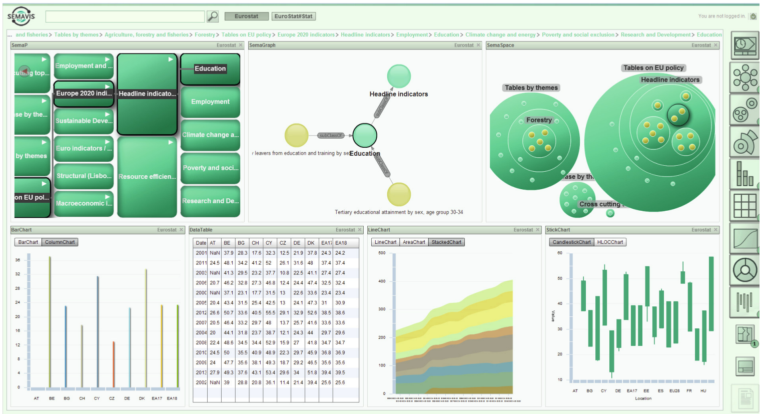

Fig. 5. Combined visualization of semantics and statistical data from the Eurostat data-base

7 Conclusion

This paper introduced an approach for visualizing social media data in an adaptive manner. The main purpose was to introduce the two complementary search and exploration paradigms: the top-down approach and the bottom-up approach in particular for the policy modeling domain. Beside the two approaches, we therefore introduced an overall model that applies visualizations to the policy modeling domain. Further, we introduced different overview visualizations that lead to a refinement of search on categorical, temporal, or geographical level. The adaptation approach was applied from an existing work [27] that includes the idea of canonical and individual user model to adapt different visual layers. We adopted the model for the search paradigm and illustrated the approach based on an exemplary application scenario.

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