Adaptive Visualization of Linked-Data

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Abstract. Adaptive visualizations reduces the required cognitive effort to comprehend interactive visual pictures and amplify cognition. Although the research on adaptive visualizations grew in the last years, the existing approaches do not consider the transformation pipeline from data to visual representation for a more efficient and effective adaptation. Further todays systems commonly require an initial training by experts from the field and are limited to adaptation based either on user behavior or on data characteristics. A combination of both is not proposed to our knowledge. This paper introduces an enhanced instantiation of our previously proposed model that combines both: involving different influencing factors for and adapting various levels of visual peculiarities, on content, visual layout, visual presentation, and visual interface. Based on data type and users' behavior, our system adapts a set of applicable visualization types. Moreover, retinal variables of each visualization type are adapted to meet individual or canonical requirements on both, data types and users' behavior. Our system does not require an initial expert modeling.

1 Introduction

Adaptive information visualization combines the areas of information visualization and adaptive systems to provide personalized and enhanced visualization. Recent research in adaptive visualizations showed significant advances in human information processing [1,2]. The adaptation techniques were in particular adopted to search and exploration task. The evaluation results of the implemented adaptive visualizations are promising, whereas the applied methods vary enormously [1,3,2]. Although this young research area has already provided interesting and promising approaches, a review on the developed systems and approaches in adaptive visualizations shows shortcomings and limitations. The first limitation refers the use of different influencing factors in adaptive visualizations. In information visualization two main aspects plays a key-role for a sophisticated design, the user with her visual abilities, prior knowledge, and aptitudes; and the main characteristics of data [4]. The adaptation of existing systems is either affected by data [5, 6] or by user [1]. A system or approach that adapts based on both influencing factors could not be found. The second limitation refers to the training of such self-learning adaptive

G. Bebis et al. (Eds.): ISVC 2014, Part II, LNCS 8888, pp. 872–883, 2014.

visualizations. The systems and approaches that are adapting to users' characteristics have to be trained by visualization experts [3]. With each new visual layout the entire system have to be trained with commonly static behavioral patterns as repeated interaction sequences. To our best of knowledge there exists no method that replaces a system-training by experts. The third and in our opinion main limitation is that the transformation pipeline of data to visual representation is not considered in today's approaches. Although there are many studies of visual perception, reference models for information visualization, and a huge treasure of methods, applications and their effects to human perception, the outcomes of these decades of work [7, 8] are not reflected in today's adaptive visualization approaches.

In this paper we introduce a novel adaptive visualization system based on our previously proposed model [9, 10]. Our visual adaptive system focuses on recommending and adapting automatically based on the underlying data and users' behavior. The adaptation process includes the entire pipeline of data-transformation to interactive visual representation. We demonstrate our adaptive visualization system on real-world Linked-Data bases.

2 Related Work

The emerging area of adaptive visualization already brought a huge number of adaptive information visualization systems that enable a more efficient, more effective, or more usable interaction with complex visual representations. Golemati et al. [11] introduced a context-based adaptive visualization that considers user profiles, system configuration and the document collection (data set) to provide an adequate visualization. The adaptation of the visualization is based on the "context" which has to be generated manually. The rules for user classifications needs experts, who have to classify this aspect manually too [11]. An implicit interaction analysis is not performed; further the use of different visual layers is not proposed. A similar approach is proposed by Gotz et al. with *HARVEST* [3]. HARVEST makes use of three main components: a reusable set of visualization widgets, a context-driven visualization recommendation and a semantic-based approach for modeling user's analytical process. The result of the modeling component is used by the integrated visualization recommendation to choose one visualization for the analytical task and is limited to just one visualization type. A further and essential limitation is the need of experts who have to define an initial design for the interaction patterns and the resulting visualization recommendation [3]. With the *APT tool* [5] and the consecutive *Show Me* system [6], Mackinlay et al. differ from the previously described works in a metaphor of small multiple displays and an enhanced aspect of user experience in visual analytics. Although they propose an adaptive visual system, the used algebra is defined for data to provide a better mapping of data-tables to visual representations. Da Silva et al. investigated the reduction of complexity by adapting the data [12]. They introduced a formal model for computing the degree-of-interest based on the main concept of an ontological data structure.

This approach is limited to adapting the visual representation based on the underlying data; the user is not investigated as influencing factor for the adaptation. The adaptation of a spatial visual presentation layer based on user preferences is proposed in the *Adaptive VIBE* system by Ahn and Brusilovsky [1]. However, their approach does not provide adaptive capabilities for various data types and is limited to one visualization type and a point-of-interest provided by the user manually [1]. The introduced examples demonstrate the upcoming popularity of adaptive visualization concepts. However, the majority of the systems use either one influence factor or adapt to one visualization or visual presentation, but the main limitation is further the involvement of either experts to model an initial visualization design or the active involvement of users' that may be obtrusive for their work. An automated visualization adaptation by adapting the different levels of visual representations (Data, Layout, Presentation) [9, 10] is not being proposed. Further, the advantages of reducing the complexity by combining visualizations, adapting their presentations and make use of data types and user behavior has not been thoroughly investigated so far.

3 Approach

We introduce in this section some elementary concepts that allow the visual adaptation of Linked-Data on different levels. Some of the following approaches were already presented in more specific ways to provide a comprehensible and replicable description. The main goal of this section is therefore to interlink the introduced approaches and illustrate how the concepts interplay with each other.

3.1 Linked-Data Retrieval and Modeling

The conceptualization of knowledge as semantics or ontology provides various enhanced features for retrieving information. This information can be explicitly modeled in a semantic knowledge base or implicitly inferred by logical functions. Semantics as formalization of information has experienced wide dissemination in Web, research, and industry. In particular the RDF-based Linked-Data formalizations have experienced a wide acceptability and dissemination in Web [13, 14]. The human access to semantics is commonly performed by various kinds of search, whereas answering simple questions about facts in form of "who", "what", "where" and "when" seems to be the focus of the semantic search approaches. To enable the process of information exploration according to Marchionini [15] by interactive visual interfaces, we introduced an iterative querying approach on Linked-Open Data (LOD) data-bases [16].

Although the data in the LOD data-bases are semantically well-defined, the amount of data is more than sufficient and their structure provides the opportunity for the usage of alternative knowledge-acquisition and interaction with semantics. Today's user interfaces of Linked Open Data do not really evince an added value to existing visualization for exploratory search. Existing semantics visualization techniques do not consider the surpluses of the Linked Open Data structures, where the semantics structure has to be built-up with a routine of query requests. They focus on various but specific ontology characteristics. The complex structure of the Linked-Data varies, based on the data-base and the way how these data are queried. The heterogeneity of the requested data should be exploited for the visualization to enable a more efficient interaction with the underlying semantics.

To gather the semantic relations based on search terms, we use the iterative querying model that starts with the search-term of the user and queries all instances for that particular term [16]. The semantic data-base returns a set of instances that contain the searched term. Each instance contains an URI for a unique identification of the instance and commonly some properties, e.g. geographical or temporal information. After that the method queries for each instance the highest concept from which the particular instance inherits. The direct querying of the highest concept (commonly called *domain*) is supported by some LOD data-bases, e.g. *Freebase* [17]. At this stage, for each queried instance the highest concept is given and each of the high-level concepts contains a set of the queried instances, whereas this is a subset of the entire queried instances. The iterative querying starts with requesting the sub-concepts of each high-level concept, where the result is a set of concepts that inherits from the high-level concept and each sub-concept contains a set of queried instances with at least one resulted instance. This approach enables to consider the amount of sub-concepts and if there exists just one sub-concept it can be ignored for the data model to reduce the interaction costs.

3.2 User Modeling

The main goal of analyzing users' interaction behavior with data and visualizations is to represent these for generating an abstract model of the behavior and provide sufficient visual adaptations. Sleeman proposed that the main aspects in modeling users are the *nature* and the *structure* [18]. Thus nature refers to user characteristics or features that are in our approach gathered implicitly from users' interaction. We constrain these features to users' interest and tasks [19, 18]. To gather such contextual information about users through their interaction behavior, we introduced an interaction analysis algorithm that allows the analysis of users' interaction to model a behavioral pattern and provide interaction predictions [20, 9, 21]. Thereby the interaction event I as a relation instantiated with leaf values of the domains equivalent to *Relational Markov Models* as $I = r(k_1, ..., k_n), \qquad k_i \in leaves(D_i) \quad with \quad 1 \leq i \leq n.$

To compute the probability distribution of users' interactions, we first determine the Steady State Vector (SSV) as a relative measurement for the occurrence of interaction events. The SSV is a normalized probability distribution with $\sum_{i=1}^{n} p_i = 1$ and therewith a probability distribution over all possible interactions. We use the frequency distribution of the interactions. The frequency distributions are computed based on the quantitative occurrence of an interaction i in contrast to the entire interactions. Therewith the probability for occurrence of an interaction i is defined as $p_i = \frac{v_i}{|A|}$, where v_i is the amount of all occurrences of the interaction i and $|A|$ is the amount of interactions the user performed previously. We use for the set of all previous interactions A either the set of interactions of the individual or canonical user [22, 21].

Thereby $leaves(D_i)$ are the leaf nodes of the domain D_i and r is a relation over the domains $D_1, ..., D_n$ [20]. This formal representation of users' interaction enables to model each interaction in a unique way and analyze them to model the behavior or measure predictions and probabilities. The probabilistic distribution of users' interactions over the different levels of abstraction enable us to measure various values for preferences and knowledge of the users. Modeling users' can be performed on a detailed level by investigating all abstraction levels of the three identified domains. We further use for the calculation of user similarities the *Pearson Correlation Similarity* [23] and for recognizing deviations, the cosine similarity [24, 23, 21].

By modeling the SSV through the semantic hierarchy and analyzing deviations and similarities, we are able to model users' interaction behavior with visual layouts and the underlying data. The canonical user model enables further a system that does not require a training by an expert form the field.

3.3 Visual Adaptation

Our approach on visual adaptation is based on the foundational work of Bertin [7], who differentiated between two elementary aspects of visual mappings: *Implantation* and *Imposition* visualization attributes that use the two dimensions of a plane (screen) to encode information through graphical marks and those, which encode information through their relationship to each other [10]. This differentiation is of great importance for adapting visualizations, which is also supported by results in cognitive science (e.g., Feature Integration Theory [8] or Guided Search Model [25]) [10]. Different and independent studies illustrated a rapid and parallel processing of the retinal variables by the low-level human vision. The so called "pop-out effect" makes use of the human's parallel vision processing and guides the attention to the related location on the screen [25, 10]. Ware proposed a three-tiered model by considering both the preattentive parallel processing and attentive stages of human vision [4]. He subdivides the attentive processing of visual information into a serial stage of pattern recognition and a further stage of sequential goal-directed processing. While the preattentive stage refers to the retinal (or visual) variables, the attentive stages require a serial (or sequential) processing of information, which can be provided by visual information of object relationships [10]. This aspect of attentive serial processing, in particular by separating the visual retinal variables and layout information, was also investigated by Rensink [10]. In his *coherence theory* and the *triadic architecture* the strict differentiation of *layout* and the low-level retinal variables was proposed in terms of the dynamic generation of a visual representation. Rensink's triadic architecture starts with the low-level vision (pre-attentive) and is generally similar to Ware's model. The most important aspect in this context is the unification of *layout*. Rensink proposed that one important aspect of the scene structure is *layout*, "without regards to visual properties or semantic identity" [26, p. 36] [10]. Further the representation is limited to the *amount* of displayed information.

The described processes of visual perception in relation to human attention are the foundation of our differentiated visual layers for adaptation. Based on the introduced models and the results on research of parallel and serial (or sequential) processing we introduce first a model for visual adaptation based on two major visual layers: *Visual Layout* and *Visual Variables* as illustrated in Figure 1.

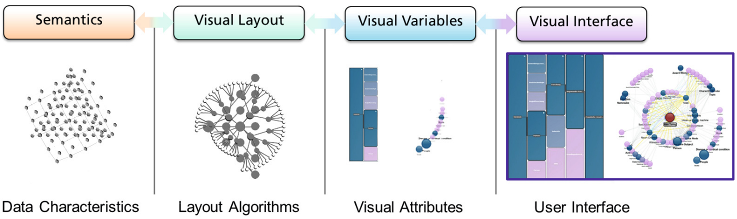

Fig. 1. Schematic illustration of visual layers with tentative examples

4 Application Scenario

The introduced approaches and methods should enable to comprehend the application scenario that is designed for exploratory visual search in LOD data-bases. Almost every one searches the Web for information. The differences between the people, who are interacting relies not only on their prior knowledge, interests, education, visual abilities, or aptitudes, the users differ in their cultural and demographic background too. The here described software was accessed by users all over the world as it was provided as open-access visual environment.

In our opinion, the heterogeneity of users in this application scenario is the main reason that visual representations of search results could not find their way to a regular usage in Web search. The common way of searching information on Web is still the list-based textual representation of search results. Although, information visualization and visual analytics experienced enormous enhancements and developments, the techniques are still just used by special groups of users for special tasks. Although, we do not expect that our system will be established as visual search environment that is regularly used and is part of the daily searching tasks, we think that the idea of adaptive visualization would enable this and our system could be a first step towards a visual search for average users.

4.1 Linked-Data Retrieval

We use in this application scenario two slightly different data-bases with their search capabilities and own servers. On the one hand the *DBPedia* data-base with the structured Linked-Data [14] and on the other hand the *Freebase* data-base a Linked-Open-Data base of *Google* [27], [17]. The search process is bottom-up by means that the user starts the search with a query. The searched term is queried on both data-bases simultaneously that leads to results from two different data-bases and provides a more complex visualization process. The search results from the semantic data-bases are commonly instances without further semantic relations or contextual information. The returned instances have commonly a weighting-value, how good the queried term matches to the results. These resulting instances are our foundation to create a visual semantics and provide contextual information. Therefore, we apply our iterative querying approach (see Section 3.1) to generate a categorical hierarchy and a contextual semantics.

The iterative querying approach [16] enables to gather and visualize the semantic structure of the result set and provides an interactive picture of the searched term. This process is the foundation of visualizing the semantic structure. In this application scenario, we enhanced our approach based on the users' search intentions. We determine based on the searched term, if a search is focused or more exploratory. Therefore the search terms are compared to the weighting values of the data-base. With the assumption that if a user searches for a specific fact, she defines more precise search terms, we implemented an algorithm that make use of the data-base weightings in relation to the search terms. If one result returns based on a specific search that may contain more than one search term is weighted significantly higher than other results, our system visualizes the entire set of results but selects the result with the highest value.

4.2 User Modeling

The visualization system starts with a canonical user that adapts the entire visual interface based on the queried data and the user model [21,22]. One main aspect is that the search is performed simultaneously on two different data-bases. Therefore the visual variables that indicate relevance values and guide the users' attention differ in their color hue. This is to enable a differentiation between the results of the two data-bases. Beside this, each visual layout on interface is annotated with the corresponding data-base. The adaptation based on the canonical user model is based on the interaction behavior of the user in relation to the data. So the results of the different data-bases may initially be visualized with different visual layouts. This is due to the different structure and content of the result data.

The canonical user model is the main user model of this application scenario and therefore, beside the data structure, the foundation of adaptation. Due to the very different data that are returned from the data-base, the adaptation effects are bigger and changes during the interaction with the system appear more often. A main aspect is that during the interaction, data may be loaded from the underlying data-bases on demand. The changed data structure in combination with the user model effects the visual interface immediately and enhances the interface with new visual layouts. Thereby the automatic dismissal of placed visual layouts are only then performed, if no data for that particular visual layout exist or the user starts a new search that returns other data with other data-structure.

In contrast to an adaptation based on the canonical user model, if a user is logged-in as individual and has not yet an individual user model or his user model does not contain enough data to determine his preferences and behavior, our approach investigates for that user the canonical user model and trains simultaneously the individual one. In this case the introduced approach of measuring deviations and user similarities [21] are continuously applied. Thereby the individual preferences of the user are measured and if his individual user model contains enough information for an individualized adaptation, the canonical user model is not investigated anymore for adaptation (but further trained) and the individual user model is applied for adaptation. To illustrate how individual user may change in their behavior, we illustrated in Figure 2 the initial results of the term *Albert Einstein* of two differing users.

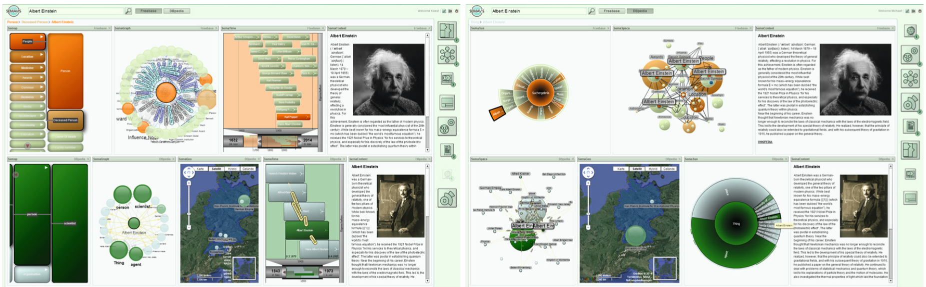

Fig. 2. Visual adaptation for differing user

Figure 2 illustrates clearly that the deviated user models of the two users affects the visual variables, visual layout, and the visual interface. Thereby the content is not adapted, due to the very specific search term that leads to an automatic selection of a uniquely identified search result as described above.

4.3 Visual Adaptation

The adaptation process changes the visual interface during users' interaction which can lead to the recommendation of different visual layouts. This effect is always coupled with the users' interaction to perceive the changes on screen as a reaction of the system. Major changes appear if the user searches for other terms, his interaction with data is loading a set of new data that has another structure and content, and in particular if the user is logged-in during the search and exploration process. Thereby the already placed visual layouts still remains, except a new search is performed. During the interaction without searching for another term only new visual layouts appear without dismissing the placed ones.

Figure 3 illustrates a scenario in which the user started a search for the term *Einstein* and navigated in both data-bases to the city of Princeton (Figure 3:a). Thereafter he logged-in as individual and the visual interface and the visual recommendation changed their appearance. The visual interface added new visual layouts, while the visual recommendation changed the order of the recommended visual layouts (Figure 3:b).

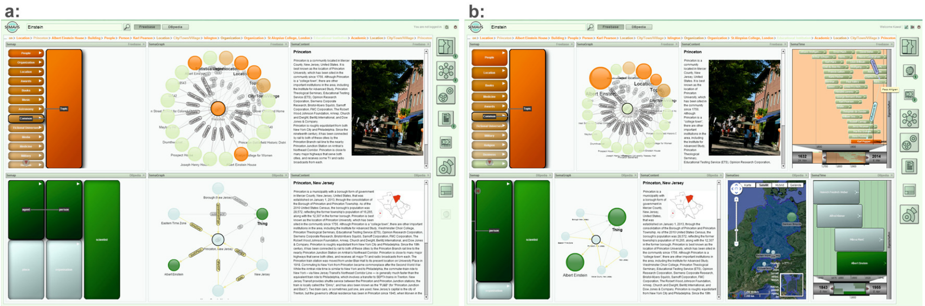

Fig. 3. Visual adaptation during the interaction process

Another mentionable aspect of the adaptation is the use of our prediction algorithm [20] in context of adaptation. Commonly our approach makes use of the algorithm to load data on demand prior to users' interaction. This procedure reduced the loading and measurement time for the adaptations. In some cases it might be useful for the user to see what is predicted by the system. Commonly this functionality is turned off, but the user can turn this on to get recommendations for interactions. Thereby commonly the underlying user model is investigated to measure the predicted action. The predicted action may lead the users' attention and guide them in his exploration process.

The content adaptation is based on the underlying user model. While not logged-in users get a kind of content recommendation based on the overall average interaction behavior, the individual users' content is recommended based on their own user model. For the content adaptation in particular the users' interests are considered and a data-base independent model is generated that is part of the user model. The steady state vector on concept level enables a data-base independent recommendation of data. This is in particular in Web search of great interest, thus the user searches and interacts simultaneously with two different data-bases. Although, the data-bases have different data-structure and differing content, on an abstract level the interactions and interests can be determined for both data-bases. However, not all concepts use the same terms and cannot consequently be matched. Commonly the content is recommended by using the visual variable layer of our reference model [28] and changes the items of interest in their size, color, order, and brightness. Figure 4 illustrates the search results for the term *Kabul* for two different users with different interests: while the user in Figure 4:a is more interested in events, the user in Figure 4:b seems to be more interested in places. In this context just one common concept (*Country*) is retrieved from the databases. Although this concept is in the two databases on different levels of hierarchy, the user model is able to determine based on the introduced algorithms the relevance of this concept for the user and highlights it.

The adaptation in this application scenario is based on the combined model of user behavior, data structure and content. It is further enhanced with recommendation functionalities and prediction of recommended data that can be turned on, if the user wants such guidance. All other functionalities like adding, dismissing, and rearranging visual layouts can be further used in this application scenario. Each interaction of the user trains the canonical user model and if the user is logged-in his individual user model too. But our application can be used as a visualization environment without the adaptive functionalities. The user has always the choice to use the adaptive version or the non-adaptive version that neither adapts the different visual layer nor recommends any visual layouts for the user.

Fig. 4. Content recommendation in adaptive visualization

5 Conclusion

This paper introduced an enhanced instantiation of our adaptive reference model ([9,10]) as an adaptive visualization application for Linked-Data on different web resources. We used a couple of existing visualization techniques, adaptation and user interaction algorithms and a technique of generating light-weight semantics to provide a novel approach for visual adaptation. The main contribution was the separation of the visual layer into content, visual layout, visual presentation, and visual interface for a fine-granular adaptation of visualizations. The integration of user models on individual and canonical level in combination with the data-attributes provided a user- and data adaptive behavior without the need of an expert to design the visual layer. The approach was designed for semantic data in Linked-Data bases. We proposed that the combination of adaptive visualizations with the generation of light-weight semantics can support users in their search and exploration tasks and improve the user experience.

Acknowledgments. This work has been carried in the FUPOL project, partially funded by the European Union under the grant agreement no. 287119 of the 7th Framework Programme. This work is part of the SemaVis technology, developed by the Fraunhofer IGD (`http://www.semavis.net`). SemaVis provides a comprehensive and modular approach for visualizing heterogeneous data for various users.

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