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Multi Visualisation and Dynamic Query for Effective Exploration of Semantic Data

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Abstract. Semantic formalisms represent content in a uniform way according to ontologies. This enables manipulation and reasoning via automated means (e.g. Semantic Web services), but limits the user's ability to explore the semantic data from a point of view that originates from knowledge representation motivations. We show how, for user consumption, a visualisation of semantic data according to some easily graspable dimensions (e.g. space and time) provides effective sense-making of data. In this paper, we look holistically at the interaction between users and semantic data, and propose multiple visualization strategies and dynamic filters to support the exploration of semantic-rich data. We discuss a user evaluation and how interaction challenges could be overcome to create an effective user-centred framework for the visualization and manipulation of semantic data. The approach has been implemented and evaluated on a real company archive.

Keywords: Semantic Web, semantic multimedia data, graphical visualization, user interaction.

1 Introduction

Organisational memory, the ability of an organisation to record, retain and make use of information from the past to bear upon present activities [27], is a key issue for large organisations. The possibility of observing and reflecting on the past is particularly valuable in highly complex domains as it can inform and sustain decision-making. Civil aerospace engineering is one example: the life cycle of a gas turbine (commonly referred to as a 'jet engine') can last for 40-50 years from initial conception until the last engine is removed from service. During this long product lifetime a vast amount of heterogeneous data is created, i.e., text reports, numeric data, images, CAD (Computer Aided Design) drawings etc. [21]. Several everyday tasks require engineers to engage in sense-making activities, i.e., "a motivated, continuous effort to understand connections (which can be among people, places, and events) in order to anticipate their trajectories and act effectively" [16]. For example, issue identification and resolution for jet engines (a task performed when a generalised issue is suspected in a product, e.g. frequent excessive wear and tear of a set of components) can require access to information contained in tens of resources, including textual repositories (each containing several dozen of thousands of texts, spreadsheets, etc.), image repositories (same cardinality), raw data (a jet engine produces about 1G of vibration data per hour of flight) and some very large databases. Engineers must go through the different repositories searching and sieving for relevant information and any piece of evidence that can confirm or disprove their current hypothesis, or browse for patterns and trends that can spark an intuition. In a word, they use dispersed and diverse data and information to build up knowledge about a specific phenomenon. The task can last for several months [8].

Currently the work of evidence gathering and meaning structuring is done manually with the support of keyword search on textual documents and querying of unconnected distributed databases. Keyword based querying in this domain is rather ineffective due to low precision/recall [17]. Moreover the long time required to read each document and manually abstracting the data to identify trends and their possible causes implies only a limited number of hypotheses can be explored.

Semantic Web (SW) technologies can be used to semanticise such resources [8]. Semantic information enables to (i) formalise the unstructured information in texts, images and raw data, (ii) reconcile information contained in different information sources via a central ontology or a series of interconnected ontologies [3] and (iii) enable information integration across resources and formats. Semantic information is being generated over large scale using technologies for a) ontology-based knowledge capture using forms [3] and b) for information extraction from text that can be ported to new corpora by a trained final users.

In this paper we explore the issue of browsing, querying and visualizing semantic information in such semantic repositories in a way that allows users to dynamically explore the data during a complex task such as issue identification and resolution. The solution provided is based on (i) the visual contextualisation of semantic information according to some easily graspable dimensions (e.g. space, time and topology) and (ii) the browsing of the displayed information by querying the knowledge base via dynamic filters that modify the visualisation in order to focus on possible trends and patterns. This approach enables exploration of information and data currently highly challenging with existing technologies (especially commercial keyword-based systems) that could save thousands of hours a year of valuable resources to a company.

The paper is organized as follows: Section 2 overviews related work. Section 3 discusses the framework, section 4 the design rational, and section 5 provides some details on the implementation. Section 6 presents the user evaluation and our findings. An outline of the future work concludes the paper.

2 Related Work

Visualization is required whenever humans need to discover and reason about complex combinations of high volumes of data (e.g., [5]). Information visualization and visual data mining is not limited to the display, but aims at supporting human perceptual abilities during the data exploration process [15]. A vast literature exists on the topic. Cluster visualization has been used in such diverse fields as intelligence (i.e.

to show correlation between people [36]) and image collection access (i.e. to show similarity in images [10]). Alternative visualizations have been used to make easy to identify patterns in homogeneous data (e.g. in geospatial data [1]); multiple visualizations, instead, map the strength of relationships between elements [4]. In text retrieval, much research has investigated the visualization of search results (see [12] and [13] for an overview), the visualization of the whole document collection (e.g., Treemaps [35]) or large text corpus (e.g. Jigsaw [26]). Information exploration, an open-ended process that is iterative and multi-tactical [18, 33] is currently gaining interest and stimulating new user interactions beyond traditional text search [34, 24].

The issue of visualization of Semantic Web (SW) data has been recognized since the publication of the seminal book [11]. A tension exists: “the Semantic Web emphasises formal, machine readable [...] approaches. It focuses on the formal and even the meaning achieved through rigorously defined forms. In contrast, information visualization emphasizes the semantics and the meaning that can be conveyed by visual-spatial models to the users.” [6]. Much research effort in semantic-based visualisation has been spent on finding ways of visualizing complex graphs that derive from the interlinking of semantic data, the relation between different concepts [28], the different granularities [31], and (dis)connections [19]. The result is a large number of ontology-based visualization systems (some are reviewed in [9]).

More recent research has tried to make use of the special features of RDF to provide end-users with intuitive ways of accessing semantic data. BrowseRDF [20] uses the faceted browsing paradigm: facets are generated automatically from the data itself; the user can constrain one or more of the faceted provided to filter the data set.

Similarly, mSpace [23] sequences lists of facets, the item selected in a list constrains the following step. Users can combine facets in different ways: this allows an intuitive composition of complex filters for the purpose of exploration.

In IVEA [30, 31] the user creates their own view over a text collection by dragging and dropping ontology concepts on a scatter plot panel. The filters provide a multi-dimensional view of the document collection as a matrix with colour coded values.

SIMILE[1] provides an interactive, web-based visualisation widget developed to demonstrate the application of SW technologies to heterogeneous metadata. It interlinks geographical mapping and a timeline to display information about the USA (past) presidents, e.g., place of birth, term(s) in power, etc.

3 A User-Interaction Framework for Semantic Data Exploration

In a SW framework, information in text, images, tables and other forms of data can all be captured and mapped to ontology concepts, instances or relations and be represented as triples. SW technologies can pull together heterogeneous material in a single unified form and create a single organizational memory out of many different and scattered archives. However, SW-based organizational memory can be huge when derived from very large collections, encompassing dozens of repositories

[1] The SIMILE Project: http://simile.mit.edu

containing tens of thousands of documents which in turn produce millions or billions of triples. A real problem in knowledge discovery occurs when making use of such extremely large data set as no human could be expected to hold all the information in their mind. Specific tools that help users explore the knowledge and draw hypotheses from it are essential for effective use of SW-based organizational memory. This requires the following fundamental steps:

1. The RDF repository has to be planned to support effective human interaction: Triples may not hold any context if it has not been captured, e.g. it is impossible to plot triples by time if the date is not there; A single ontology should map heterogeneous material into a single representation.
2. The visualization has to be intuitive to properly contextualize semantic data and the interaction tools have to be easy-to-use to support exploration and knowledge discovery, e.g. space and time contextualize semantic data in an intuitive, factual way.
3. Tools to facilitate data annotation should be smoothly integrated in the interaction flow to guarantee a sustained improvement of the quality of the repository along its use, especially when data is generated using automated means (e.g. by applying information extraction on legacy data).

In this paper we focus on the second point and propose the use of multiple visualizations as a way to help users explore, discover and reason; find confirmation of their intuition; and drill down to the data level when needed.

As discussed in the next section, the dimensions of visualization should come from the ontology and the values for each dimension from the semantic repository. Dimensions should be then mapped onto a structure that is appropriate for the final user. For example the dimension 'date' can be structured as a linear timeline (as done in this work) or as a calendar, e.g., to visualize publications. Both visualizations map the same semantic data but serve two very different user purposes.

Some dimensions are generic and likely to be valid across a wide range of applications. This is the case of time and space. Other dimensions are valid across a subset of domains, for example this paper uses topology, useful in engineering where a machine of some sort is the core of the domain ontology. Finally the user may define their own perspective, e.g., time and a continuous attribute could be plotted to facilitate the monitoring, for example, of financial markets.

4 Knowledge Visualization and Manipulation

For data and information visualization, Shneiderman advocated tools that provide the user with a progressive focus: "overview first, zoom and filter, then details-on-demand" [25]. The overview is to gain a sense of the whole data set; zoom and filters are used to focus the attention on (potentially) interesting patterns; details on demand to drill down to the level of single data and carefully inspect the content.

This section discusses our proposal for a concrete visualization of semantic data. This visualisation complements ontology-based visualization, as it reduces the cognitive effort needed to understand the semantic data.

We adopted a user-centred iterative design approach [8]. The design rationale discussed in the next section emerged after workshops and observations with users aimed at collecting requirements, and a number of participatory design sessions with engineers in which layout and interaction were refined to maximise their usefulness. In opposition to the generic trend of using a single visualisation to display semantic data and its connection, we contextualize data in multiple, complementary and inherently different visualizations where each "view" offers a perspective over the data: the user dynamically filters the data and moves from one view to another while following a personal investigation trial.

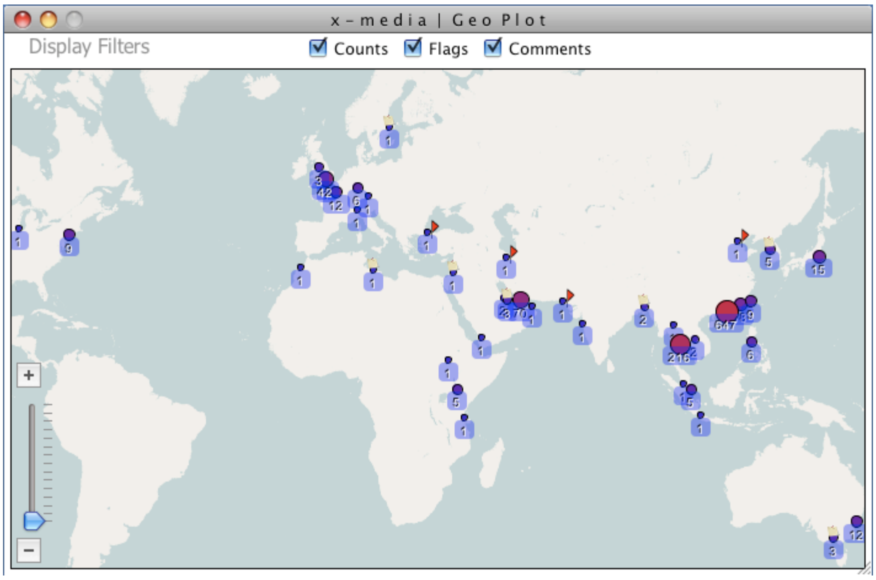

Figure 1 The triple-store displayed on a world map - dots, flags and notes add meaning. The numbers in the map indicate the number of cases found per location. The filters used are identical to those in Figure 2.

Figure 1 shows the GeoPlot of 34,750 triples extracted from 4,958 event reports that are part of Rolls-Royce's organisational memory[2]. The extracted triples are displayed on a world map showing the distribution of events; the size of the dots codifies the number of events. Flags and comments can be added to keep track of personal intuition during the sense-making process.

Fundamental for effective exploration is the dynamic update of the display when the user manipulates the filters, called dynamic querying [2]. The filters (Fig. 2, left) allow the user to quickly set the parameters of interest and immediately see the effect

[2] These are just a fraction of the triples that we generated from Rolls-Royce organisational memory. They were extracted by semi-automated information extraction and machine learning as part of a general effort to semanticise their legacy data. The final data set holds several hundreds of thousands of documents and covers several different types: one-page reports sent from all airports in the world covered by the Rolls-Royce service agreements, extended reports of workshop inspections, technical updates, workshop photos, tables, etc.

on the display (Fig. 2, centre). The filters' interactive features depend on the data type: a slider to set a range for numeric data; a text field to enter codes; a single selection list items and group of check boxes for multiple selection. The result of the filtering is dynamically plotted: in Figure 2 the blue (darker) crosses match the query (multiple filtering), while the gray (lighter) ones are triples outside the result set. Filters on one visualisation are applied to all the others simultaneously in order to maintain consistency. The geographical and the topological visualization needs two dimensions, but the TimeLine is uni-dimensional and therefore the Y axis can be dynamically changed using drag-and-drop with any concept from the ontology (Figure 2, right) onto the plot.

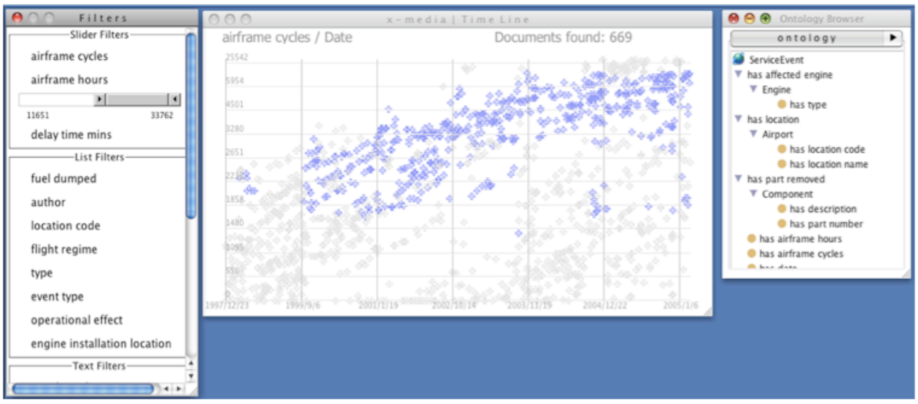

Figure 2 The dynamic query filters (left) set the values for the TimeLine (centre). The X-Axis is time, the Y axis is the number of airframe cycles; the top right the number of matching documents.

A third visualization uses topological information, in our case a TopologicalPlot, as intuitive dimension to plot triples. Figure 3 left shows an engine overview: gray areas correspond to high-level ontology concepts. Hovering on an area shows a summary of the documents mapped to this engine part; clicking on the area opens a detailed map of that part where the documents are plotted, Figure 3 right, respect to finer grained concepts, the engine components. Their position is as faithful as the ontology allows, that is to say, the finer the grain of the ontology concept the more precise the position of the cross on the graph.

The three visualisations, TimeLine, GeoPlot and TopologicalPlot show the same data with respect to different dimensions that complement one another. The structure itself can be semantically enriched therefore adding new knowledge to the visualization that is not present in the data, i.e. providing semantic services attached to the world map. The visualization could be enriched father by coding properties the user wishes to monitor in a more salient and graphical way, e.g., suppose the user is interested in instances of the concept 'wear', an event often associated with sand friction, then these events could be highlighted in red and a GeoPlot can easily show their pattern in deserts regions.

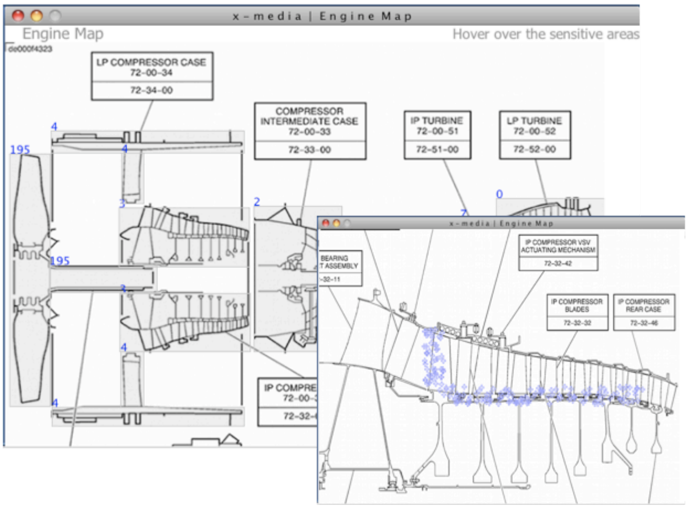

Figure 3 The TopologicalPlot: each component in gray in the Engine Map (left) can be clicked on to zoom-in a more detailed view of the information associated to its subcomponents (right). Numbers is blue show the total count of issues identified per component. The filters are the same as in Figure 2.

5 Implementation

The starting point is an existing semantic repository (triple store) and its related ontology; interactive filters are automatically generated on the basis of the data found in the ontology. Data tables are created where each row is a document in the dataset, and each column is a concept annotated within the document. In Figure 4, the attributes *hasFormattedEventDate*, *hasLocation*, *hasComponent* are extracted to build TimeLine, GeoPlot and TopologicalPlot respectively.

While only some of the ontology concepts and relations become visualization structures, all of them become filters. The data table is read and each column is converted into a graphical widget, which one depends on its value range. A core set of filters, with different interaction affordances, is used to capture different aspects of the data set: sliders are used to define ranges of continuous data; text input is used to capture meaningful strings, e.g. engine serial number; check boxes and menus for selections in a closed set, e.g., *hasTSN* and *hasCSN* are mapped onto a slider; *hasEngine_Serial_Number* uses a text field; *hasRegime* uses a group of check box.

```
<rdf:Description
rdf:about="http://kmi.open.ac.uk/projects/xmedia/RR1.owl#Event_Report.BKK.Event_Report_237">
<rdf:type rdf:resource="http://kmi.open.ac.uk/projects/xmedia/RR1.owl#Event_Report"/>
<j.0:has_file_location>BKK/Event_Report_237</j.0:has_file_location>
<j.0:hasFormattedEventDate>26-Jul-1922</j.0:hasFormattedEventDate>
<j.0:hasEventDate>26-Jul-22</j.0:hasEventDate>
<j.0:hasAssociatedDate>28-Aug-22</j.0:hasAssociatedDate>
<j.0:hasTSN>14613</j.0:hasTSN>
<j.0:hasEngine_Serial_Number>ESN12345</j.0:hasEngine_Serial_Number>
<j.0:hasLocation>BKK</j.0:hasLocation>
```

```
<j.0:hasRegime>GROUND</j.0:hasRegime>
<j.0:hasCSN>5362</j.0:hasCSN>
<j.0:hasComponent>Fuel Metering Unit</j.0:hasComponent>
</rdf:Description>
```

Figure 4 An example of the annotations of a document in RDF format. (Values shown are realistic but fictitious and do not correspond to a real instance of an Event Report.)

Different toolkits have been used to build the visualisation modules. Prefuse [14], an interactive visualization toolkit with sophisticated visual features is used for the TimeLine. The X-Axis represents time, and the Y-Axis a continuous numeric value such as CSN ([flight] cycles since new). The user can dynamically change the Y-Axis concept using drag-and-drop from the ontology. This enables all the ontology concepts to be plotted against the timeline. A visibility filter controls the display of each visual item: the ones in the filtered set are highlighted, the others are greyed out.

The GeoPlot visualization is generated using the JXMapKit API that plots geographic coordinates on a world map downloaded from OpenStreetMaps.com. The geographic locations are airports, identified by their IATA (International Air Transport Association) codes, as extracted from the dataset. The IATA codes are used to automatically find the airport details such as geo-coordinates (used in the plot), airport name, city and country. The size and colour of the waypoints are calculated on the number of visual items associated with the airport.

The Topological Plot is composed of two interactive maps manually created using drawings from an engine user manual. For the top level, selected regions are annotated with high-level ontology concepts corresponding to the engine parts, each showing the number of visual items associated with the concept. A detailed view of the part is displayed on click; this drawing too has been manually annotated with finer grained concepts from the ontology that corresponds to engine components. Although the maps have been manually created it is easy to imagine a situation in which the CAD drawings of an engine has semantics associated and therefore the generation of the maps is automatic.

6 User Evaluation

The usability of the visualisation and manipulation was carried out. Results are used to adjust and re-design the system before it is deployed for a monitored field trial at Rolls-Royce plc as an additional support to actual investigations. While the trial allowed us to measure the impact this technology has on real practice and observe its use in a naturalistic setting, the user evaluation reported here focuses on assessing its usability, that is to say to find out what works and what instead could be perfected. This ‘evolutionary’ approach to user evaluation, from lab to the field, has proved to be robust for the development of new technology for professional use [22].

6.1 Setup and Procedure

The user evaluation was set up to assess the usability of the visualisation and dynamic querying of semantic data. 12 participants took part in the evaluation and were recruited by acquaintance, they were 4 women and 8 man, their age ranged from 25 and 45, they were PhD students and researchers; 3 participants were aware of information visualization tools but none had used any. As the time of professional engineers is a limited resource and the focus of this evaluation was the usability we considered the sample acceptable for the goal at hand. Participants carried out a number of small tasks to determine if:

1. The visualization mechanisms supported knowledge discovery: patterns were to be found in the data that could represent phenomena of interest;
2. The dynamic queries were intuitive to use: participants were required to manipulate different types of filters, slider, checkbox, text;
3. The overall visualization and dynamic queries strategy were usable.

The test was done individually. At arrival participants were introduced to the project and the purpose of the user evaluation. They were talked through the main features of the visualization and manipulation by an evaluator. Then participants familiarized themselves with the system using 7 simple, 1-step tasks covering the three visualizations and the filters. An indication of which visualization(s) was the most appropriate and how to use it (them) was given for each task. During the training participants could ask for explanation or support from the experimenter. Participants were then requested to carry out another 8 tasks on their own: each of these tasks asked the user to perform 2 or 3-steps, for a total of 18 steps. These tasks were slightly more complicated than the training to stimulate more articulated interactions and were designed to test different aspects of the system. Flexibility is a key point for user acceptance and we wanted to find out if our solution accommodated personal attitudes. Task distribution per visualization is reported in Table 1, T-TimeLine, G-GeoPlot, E-TopologicalPlot, and ALL the visualizations; C-F is for commenting and flagging in the GeoPlot.

The tasks were designed for users with no expertise on jet engines and did not require participants to understand the content of the documents that could be displayed on click. As users were not experts they were not required to identify trends directly, however the tasks used simulated the ones that an engineer will perform in order to identify trends. They generally required to identify (geographical, time or topological) areas where the count of events was either clearly above average or had specific characteristics. Most tasks were cumulative (i.e. they built on the results of the previous tasks) so to simulate a multi-step investigation.

Examples of cumulative tasks are[3]:

a) How many documents refer to the **registration number** *9V-SQD* with number of **airframe cycles** *>6500*?

[3] Tasks are simplified here for the sake of clarity of exposition. Task b) was to be performed on the results of a); c) was to be performed on information retrieved in b)

b) `Consider only what happened in` ***`SIN (Singapore),`*** `how many events occurred there?`

c) `Which component seems to have the highest number of cases associated with the` **`flight regime`** *`CLIMB`*`?`

These tasks required the use of the different tools and strategies while performing each query:

a) The registration number requires entering text in a form field, setting an airframe cycle number requires manipulating a slide.
b) Requires to interpret the previously retrieved data by focussing on a specific area of the GeoPlot
c) Requires now to move to the topological display and to drill down to the level of components. Flight regime is a checkbox.

The tasks enabled to measure all the available interactive features in a limited test time of 30-40 minutes. During the test the screen activity was recorded for further data analysis.

At the end of the evaluation participants were requested to fill in a user satisfaction questionnaire composed of 16 closed and open questions. Close questions were on a 5-points scale and addressed the system overall, its learneability, the task flow, the result display, the system's speed and reliability. Open questions asked about the most positive and negative aspects of the system. No questions focussed on comparison of visualizations as all three have been seen in use during the user requirements phase: timelines in presentations to summaries observed phenomena; geographical information was reported as one of the first inquiry done; and maps of the engine covered in post-it and annotations hung in meeting rooms. We are therefore confident on the usefulness of all three.

6.2 Analysis and Results

The results are analysed with respect to: efficiency, effectiveness, and user satisfaction (as in the ISO definition of usability [32]). Minor issues of interface inconsistency across the three visualizations were also identified, e.g. display of the number of results in the set displayed in different positions in the three panels. Both objective, numeric data, and subjective data, participant's opinion, have been analysed. Qualitative analysis, i.e. observation of participants' interaction, has been used to explain qualitative results, i.e. statistic on numeric values.

Efficiency has been calculated on the time participants needed to finish **a task** (that could include few different steps). Performance in both training and test varied greatly from task to task and from participant to participant, and from a min of 18 sec. to a max of 420 sec. Table 1 shows this variability by task, Table 2 by participants. The average time to complete a test task (including the time to think how to solve the task) was 87 sec. The average time for a simple 1-step training task was 67 sec. while the average time spent for complete 1-step during the test was 46 sec. showing an increase in efficiency after only an average of about 8 minutes training. The good efficiency is reflected on participants' opinion collected in the questionnaire: 82% rated the system speed very high.

On average, interactions with the GeoPlot lasted longer than other visualizations: T= 147 sec.; G=200 sec., E=138 sec. (cumulative values for participant, task only); however this is not statistically significant (one-way repeated measures ANOVA on time on T, G and E). Observation of the interaction shows that some users had difficulties in manipulating the GeoPlot: when zooming-in they were too fast and found themselves, for example, in Africa instead of Europe. Then, instead of zooming-out they preferred panning, an action that requires more time.

Table 2 shows the average time per participant. Variability among participants emerges during task with a polarization in two groups. Observations of the interaction behaviour showed different strategies with faster participants setting all the filters at once and then exploring the visualization and the slower participants going step by step, i.e. setting the value of one filter then look at the result than set a second filter. Multi filter selection was not requested during training. Flexibility of use is one of the main requirements of any data exploration environment; therefore we consider this a positive result showing user could adopt personal strategies despite time differences.

	Min.	Max.	Mean	Std.Dev.
Training 1 (T)	18	320	57	85
Training 2 (T)	20	60	32	12
Training 3 (G)	30	240	80	55
Training 4 (G)	15	200	84	50
Training 5 (C-F)	30	420	94	106
Training 6 (E)	20	120	55	30
Training 7 (E)	40	180	67	41
Task 1 (ALL)	20	240	125	81
Task 2 (T)	20	120	70	33
Task 3 (T)	25	150	77	36
Task 4 (C-F)	80	300	211	68
Task 5 (G)	50	300	122	81
Task 6 (G)	60	145	93	26
Task 7 (E)	15	100	52	24
Task 8 (E)	30	210	82	58

Table 1. Time on task in seconds. Each task was designed to test some features of the approach. The letters in parentheses describe the types of tools that the user was expected to use to perform the task in an appropriate way. All the users used at least the expected tools to carry out each task.

	Mean (sec.) Training	Mean (sec.) Task	Mean (sec.) Training + Task
P1	88	127	110
P2	71	89	82
P3	170	119	141
P4	53	71	63
P5	33	78	59
P6	85	153	124
P7	52	136	100
P8	71	128	103
P9	68	66	67
P10	33	85	63
P11	35	103	73
P12	50	76	65

Table 2. Average time per task for each participant.

Effectiveness is calculated on the accuracy of the answer provided as every task had a correct answer identified in advance. In 74% of tasks the exact answer was provided. The effectiveness rises to 82% when the simpler tasks of the training set are included. All wrong answers were 'near miss', i.e. participants incorrectly selected a value on the slide or selected the wrong value for a filter due to very similar spelling. Minor changes in the interface are needed to avoid unintended mistakes. Moreover we do not expect to see any spelling problems in field use as users knowledgeable in the domain would not mistake terms. Effectiveness was also affected by data density: some participants instead of zooming-in to gain a clearer view selected the wrong set in dense GeoPlot display.

Overall the approach emerges as effective in supporting the user browsing through a triple store, as the mistakes were due to interface issues that are easily fixable; this is confirmed by the fact that the errors were scattered and not linked to any specific condition, i.e. visualization or user.

User Satisfaction Overall participants' opinion was positive; the system was judged easy (64%), satisfying (64%), stimulating (82%), fast (82%), and reliable (91%). While this result shows a very high level of engagement and trust (mainly in the stimulating judgement), it also points out to usability problems due in part to (i) some sub-optimal interaction strategy participants adopted to perform the tasks and (ii) interface limitations, that will be discussed below. Discussion with users showed that the latter accounted for the largest majority of the difficulty the user found (affecting the judgement on ease of use and their satisfaction). The dissatisfaction was not related to the general idea and users commented that – if the issues were fixed – their judgement would have changed.

Both issues above can be easily addressed: the first with a more extended training (which will be in any case given to the engineers); the second by re-designing the weak points in the interface.

Three questions addressed learnability: participants judged it easy to learn (82%), easy to explore (75%) and straightforward to use (63%). This last value was, again influenced by the same difficulties in manipulating some graphical elements. The task flow was considered easy to start (73%) and carry on (90%) while the manipulation of the results was problematic for some of the participants. 35% found the manipulation easy or very easy, 45% were neutral and 20% considered it difficult. Again, there is a dichotomy in judgement between the recognized value of the tool and the practical difficulties in manipulating it. Observations of the interaction and the comments left in the questionnaire "most negative aspects" explain this fact: as the values on the interface come from the RDF data, the values on the slide were not continuous nor the progression smooth. This was quite confusing for some participants who tried hard to set the slide to an inexistent value, e.g. the first value for 'airframe hours' (Figure 2) is 4350 but the slide starts from 0 so there is no change in the display until the user scrolls to 4350, that is halfway through the slide. This point can be fixed in the redesign by creating a tagged-slide that highlights the valid values (from the RDF) on a standard continuous slide.

The judgement on the browsing of the results was split: 45% judged it easy, 45% were neutral and 10% find it difficult. Observing the interactions we noticed that participants who lamented difficulties had problems in selecting the right graphical element: In the GeoPlot dots representing two different airports could overlap making it difficult to select one airport over the other. When the overlap occurs the correct interaction is to zoom-in but some participants did not use it despite having been demonstrated the feature before the test. Another point of difficulty occurred when documents were very dense, as for some engine components. I this case the zoom-in (enlarging the picture) is not effective in discriminating instances as the action does not add further details. A further level in the ontology would allow mapping to a more detailed drawing of the component and therefore a finer localization of the triple on the engine spatial representation. Alternatively instances can be listed: selecting an element highlights its position on the map and double clicking would open it.

Two open questions asked for the most negative and more positive aspects of the system. Besides the already mentioned problems with the slide, listed as negative, participants did not like to scroll up and down the filters (the list can indeed be very long if filters like the airport location is left open) and found some of the filters name cryptic. This last comment does not hold for professional engineers, as they are familiar with the data.

Appreciated across the whole sample was the tidy design of the interface, its intuitiveness and the instantaneous reaction and change of display after a new filter has been set, all features listed in the open question "most positive aspects". In addition participants commented positively the fact that the filter manipulation changes the three visualizations simultaneously therefore supporting an active engagement in the data exploration activity by simply swapping view.

6.3 Discussion

The user evaluation showed that the approach is efficient and effective and the interaction largely intuitive even with very limited training. Users found the approach stimulating and were able to identify trends in the data via interactive querying. The methodology used showed this in an indirect way: as participants were not experts in the domain, the tasks simulated the querying path that an expert would follow in order to identify trends. The simulated exploration paths have been observed and discussed with users, therefore the successful completion of the tasks would provide material to an expert for the identification of trends.

Some limited aspects of the interface needs some degree of re-design as the simple action of taking the data out of the RDF repository and into the user interface may produce a less-than optimal interaction, i.e. slides don't have a smooth progression but more of a 'jumpy' interaction style. Data-generated interactive filters and dense data display need careful considerations and specific interaction-design strategies particularly when scaled up to hundreds of thousands of triples displayed. Indeed what appeared to be critical is the combination of very dense semantic data onto small space and the tendency of participant to not zoom-into the detail to clarify the vision.

A research question concerns efficiency and effectiveness with respect to the technology currently available to our final users. We believe that the approach has the potential to save thousands of hours a year of search time (efficient) and to provide a way to more widely explore different hypotheses and therefore to discover more trends and patterns (more effective). We derive this by reflecting other evaluations where users performed similar tasks using other types of technologies, both semantic and more traditional. Performing the same tasks using traditional keyword-based searches would have required several weeks of searching and manually collating information[4]. Also, our approach is more effective because as side effect of efficiency users are enabled to explore different hypotheses and therefore to discover more trends and patterns. Such extensive exploration is currently largely impossible due to the scarce efficiency of the current methodologies (exploring more hypothesis means more time dedicated to the analysis, an often impossible task under the time pressure

[4] This estimate is based on discussion with real users and direct observation of working practices.

that some knowledge management tasks are worked under). Moreover traditional methods carry imprecision due to tiredness, which affects the quality of results on very long task.

Performing the same tasks with a semantic search-based system (e.g. [17]), would have required some days of work to extract different pieces of evidence and to group them manually around trends[5]. Questions like "which component reported most issues" would have required several dozens of queries.

7 Conclusions and Future Work

In this paper we proposed to complement the ontology-based, graph-based perspective with views that contextualise the concepts into vertical dimensions, like time, space and topology. The list of dimensions that could be used for this purpose is not exhaustive and others than those we used could be identified (mostly domain-specific). The different visualizations are created starting from the RDF data and, like a kaleidoscope, show different views on the same data set. Direct manipulation complements the display and engages users in the exploration: dynamic queries generated from the data are used to instantaneously change the visualizations.

Our aim was to provide a largely automatic way to visualize semantic data and support users in dynamic exploration and manipulation. We used the case of an existing organisational memory and complex knowledge management tasks observed in real work situations, i.e., issue identification and resolution in aerospace engineering. The user evaluation has demonstrated that this automatic mapping of multiple, context sensitive visualizations to ontology-based information stores provides an efficient way to display the result of complex queries that can combine several attributes. Moreover users can explore the result and effectively detect patterns and trends. The combination of powerful multiple, contextual visualizations and a highly dynamic interaction allows the exploration of semantic data to be carried out at scale. We have shown how our visualisation approach improves in terms of efficiency and effectiveness with respect to technologies that are currently available to our users, i.e. keyword-based search and semantic search. To our knowledge this is the first study to show that using multiple visualizations is effective for document sense making in a complex organisational memory.

In our experience large organizations are willing to invest in semantic technologies for knowledge management, if they see a clear benefit and it is sustainable. The set of 4,958 documents used in this study correspond to a small chunk of the archives we are currently considering in the context of Rolls-Royce plc, but was instrumental to show the clear benefit of this innovative technology over the current practice. At the time of writing we are working in partnership with the company to extract information from large and heterogeneous archives and create a new semantic data set to support a field trial in the context of real practice. In the perspective of

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[5] This estimate is based on observation of search behaviour of users during the evaluation of the semantic search system.

sustainability, we have already developed a technology to provide ontology-based knowledge capture using forms [3] and we are studying information extraction methodologies that can be ported to new corpora by a trained final users. In light of the experience above, the approach and tools proposed in this paper are deemed extremely useful as they allow engineers to rapidly make sense of the information and data.

The next prototype will incorporate the changes in the user interface pointed out in this study and will be applied to a larger and heterogeneous data set with the perspective on incrementally increase the size of the repository when new semantic data will be made available. Tests done on much larger document repositories show no particular strain on the technique adopted. A field trial at Rolls-Royce premises in Derby, UK, with the new prototype and new data is planned for the autumn and will last for a few months.

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