Visualizing Ontologies – A Literature Survey

Arash Saghafi
Sauder School of Business
The University of British Columbia, Vancouver, Canada
arash.saghafi@sauder.ubc.ca

ABSTRACT

Information, as a representation of the “real world”, is required to faithfully demonstrate the relevant aspects of the application domain. To describe the structure of a domain, various fields have employed ontological models. Visualization of the said ontologies can improve tasks such as understanding of implicit knowledge as well as information alignment. The present work provides a survey on the methodologies proposed for visualizing ontologies in the literature, and also performs a statistical synthesis (i.e. meta-analysis) to quantitatively review some of the empirical studies that focused on the impact of visualization enhancement.

Keywords: Ontology, visualization, survey, meta-analysis.

Index Terms: K.6.1 [Management of Computing and Information Systems]

1 INTRODUCTION

Ontology is a “branch of philosophy [that] deals with the order and structure of reality in the broadest sense possible” (Angeles 1981). Considering that information systems are representations of applications, practitioners as well as researchers in information sciences have used ontologies as guidance to describe the order and structure of domains in order to develop more faithful representations of reality (Wand and Weber 1989, Shanks et al. 2008, Recker et al. 2011). Domain ontology is defined as a set of concepts, the relationship between concepts, what can happen, and what can exist - the axioms (Wand and Weber 2002).

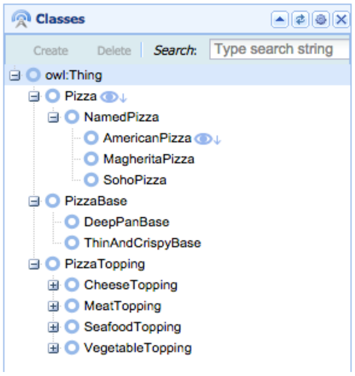
Diverse fields such as biomedical informatics, systems engineering, and semantic web[1] have developed ontologies to represent the semantic meta-data within their fields. One of the largest ontologies available is the ontology of the DBpedia project, which is a manually created cross-domain ontology with over 4.2 million resources (things) in the ontology[2].

Visualizations of ontologies have been proposed in prior research (Mutton and Golbeck 2003, Lanzenberger et al. 2010, Bera et al. 2011). Visualization in general is created to augment human capabilities in performing a task (Munzner 2014). Some of the tasks that can benefit from visualizing ontologies could be implicit knowledge identification in a domain (e.g. Andronis et al. 2010; Bera et al. 2011), integration of data sources (e.g. Granitzer et al. 2010; Parsons and Wand 2003), and understanding a domain in general (e.g. Mutton and Golbeck 2003).

The objective of this paper is twofold: (1) Survey the existing literature focusing on visualization of domain ontologies. And (2) synthesize the data from similar empirical experiments evaluating different ontological visualizations (i.e. meta-analysis).

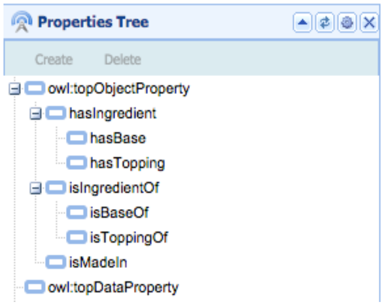
2 ONTOLOGY LANGUAGE AND BASELINE REPRESENTATION

The standard language for developing ontologies, according to the World Wide Web Consortium (W3C) is the Web Ontology Language or OWL (http://www.w3.org/2001/sw/wiki/OWL). The most widely used tool creating and modifying ontologies is an open source program called Protégé (Gasevic et al. 2009), – developed and maintained at Stanford University[3]. The ontologies created in Protégé are represented as indented trees (or lists), similar to the structure of files in Windows Explorer (or Finder in Mac OSX). In OWL, it is assumed that the building block of the world is the class called “Thing”; this set includes all instances in the relevant universe (http://www.w3.org/2001/sw/wiki/OWL). The other classes in the domain ontology are defined based on the properties that they posses. All the classes in the ontology are assumed to be subclasses of “Thing”. Figure 1 illustrates a hierarchy of a sample ontology that models a pizzeria, while Figure 2 shows the properties in this domain.



- owl:Thing
  - Pizza
    - NamedPizza
      - AmericanPizza
      - MagheritaPizza
      - SohoPizza
  - PizzaBase
    - DeepPanBase
    - ThinAndCrispyBase
  - PizzaTopping
    - CheeseTopping
    - MeatTopping
    - SeafoodTopping
    - VegetableTopping

Figure 1. Classes of the pizza ontology in Protégé



- owl:topObjectProperty
  - hasIngredient
    - hasBase
    - hasTopping
  - isIngredientOf
    - isBaseOf
    - isToppingOf
  - isMadeIn
- owl:topDataProperty

Figure 2. Properties in the pizza ontology

3 SURVEY OF VISUALIZATION METHODS IN THE LITERATURE

As part of research for the presented work, three literature surveys on visualizing ontologies were identified. The first, and most

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[1] http://protegewiki.stanford.edu/wiki/Protege_Ontology_Library Accessed on 27/10/2014

[2] http://protegewiki.stanford.edu/wiki/Protege_Ontology_Library Accessed on 27/10/2014

[3] http://protégé.stanford.edu accessed on 26/10/2014

influential[4], survey was done by Katifori et al. in 2007. They presented methods tailored for visualizing ontologies, as well as other techniques (for different contexts) that could also be used to display ontologies. They also performed an emprical user study (Katifori et al. 2006), by testing four different visualizations – all of which were plug-ins in Protégé. Two of the methods were based on indented-lists (hierarchies), and the other two were node-link based. The experimental task was investigating evolution of entities in an ontology over time. They found that users of Protégé class browser (indented lists) perform this task with higher accuracy.

Another survey was done by Lanzenberger et al. in 2010. Their purpose was to identify techniques that could be used for the task of ontology alignment, or in other words, reconciling the meta-data from various sources (i.e. interoperability). Their focus was mostly on graph-based visualization tools, whether 2D or 3D. At the end, they concluded that a compelling method that utilizes the screen real estate appropriately, while being intuitive to users, is yet to be developed.

The third survey (Granitzer et al. 2010) also focused on the task of interoperability. They studied various Protégé plug-ins that enabled reconciliation of two or more distinct ontologies. Similar to the previous survey, after discussing the strengths and weaknesses of the current approaches, they stated that the field lacks a comprehensive technique for ontology alignment. They described the appropriate approach as a semi-automatic technique that would utilize human judgment and at the same time, handles complex and evolving ontologies.

For the purpose of current work, 21 papers were identified that had investigated methods to visualize ontologies. One of the selection criteria for these papers was their exclusion in the surveys done by Katifori et al. (2007), Lanzenberger et al. (2010), and Granitzer et al. (2010). The publication date of the collected papers was in the period of 2003-2014, with the majority being published after 2011. Out of this pool of 21 papers, 11 of them had done some sort of empirical user evaluation. These evaluations ranged from lab experiments to interviews and protocol analyses.

The review in this work groups the studies based on similarity of methods and presents them in the following sections. In each group of similar visualizations, the methods are discussed by the chronological order of publication.

3.1 Graph-based Methods

3.1.1 Spring Embedded / Force-Directed

Mutton and Golbeck (2003) used a spring embedding algorithm to draw the ontology as a graph. This visualization is similar to the force-directed placement visualization (Munzner 2014; Brandes 2001), in which each class in the ontology is considered a node, while the links of the graph represent the relationship between classes in the ontology – that is whether a class is subclass of another, sibling class, or completely disjoint from the other class (declared by a closure axiom in OWL).

This algorithm considers visualizing an ontology similar to simulating a force system: the nodes act as charges particles, thus the repulsive forces between the nodes in the graph imposes a layout where similar nodes end up being placed closer to each other. This visualization is most useful for the task of identifying similar concepts in a domain ontology, as similar concepts will be found in a cluster within the spring embedded graph. Figure 3 illustrates such visualization of an ontology.

Figure 3. Spring embedded graph visualization of ontologies

Vercruysse et al. (2012) proposed a similar visualization (i.e. force-directed graphs) for ontologies. Their data source was biomedical ontologies available on the Ontology Lookup Service (OLS) database. The task that they investigated in their paper was just browsing ontological graphs by the users (as uses of ontologies in biomedical research are diverse, and this paper did not want to limit the scope to one specific task). A force-field graph visualization grants the users flexibility in the way they view the ontologies (and sub-ontologies), as the graphs can be reorganized smoothly, and enables moving the concepts "towards more optimal positions" (Vercruisse et al. 2012, p. 4) in the canvas, hence improving the exploration of bio-ontologies.

The idiom of spring-embedded graphs is summarized in table 1. This analysis framework is borrowed from (Munzner 2014).

Table 1. Spring-embedded Graphs Summary

Idiom	Spring-embedded graphs
What: Data	Ontological data as graphs
What: Derived	Classes as nodes, relationship between classes as links
Why: Task	Identification of similar concepts and browsing ontologies
Scale	Limited (up to 50 nodes at a time)

In a more recent paper, Fu et al. (2014) empirically evaluated spring-embedded graph representations versus indented lists using eye-tracking method with 36 subjects. Their justification for their evaluation was that "a lack of scientific evaluations of existing ontology visualization techniques could be potentially damning to the advancement of this field as a whole, as we may fail to recognize and adopt good designs, or to identify and reject bad practices" (p. 1).

Fu et al. (2014) found that indented lists are more efficient in tasks involving information search – defined by the authors as tasks "where [subjects] only need to sample a small amount of objects to complete" (p. 7), while information processing tasks – interpretation of information that are measured by duration of eye fixation – are done more efficiently using graph based representations. They also measured accuracy (i.e. error rate) and completion time. Completion time was faster for indented lists, however accuracy was not significantly different between the two visualization methods.

3.1.2 Clinical Outcome Search Space (COSS)

As mentioned earlier, one of the tasks that could be facilitated by visualizing ontologies, is identification of implicit knowledge within a domain. Andronis et al. (2011), used ontologies in biomedical domain for the task of drug repurposing (DR). They

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[4] Cited 293 times based on Google Scholar data, as of 01/12/2014

posited that instead of researching and developing new drugs, biomedical practitioners could utilize ontologies of existing drugs, and test different hypotheses regarding their effects. The premise of this study is that complete and comprehensive ontologies of drugs are available to researchers. They developed a mining technique for drug repurposing called Clinical Outcome Search Space (COSS), which acts as a semantic reasoner; COSS analyses ontologies and establishes similarities between various drugs and the symptoms they treat. Using graph-based techniques with colour coding, they visualize the drugs that could be repurposed. It should be noted that COSS is not an ontology visualization technique, but a visualization of inferences made on ontologies. Figure 4 shows the relations detected between two genes within an ontology.

Figure 4. COSS graph-based visualization

3.1.3 Graph formation based on Information Richness

Motta et al. (2011, 2012) suggest a graph-based approach, in which the effectiveness of 'sense-making' of the topology of an ontology will be improved. In their method, they place the concept with highest information richness – measured by density of properties and taxonomic relationships of a concept – at the centre of the graph. Using a 'middle-out' approach, their proposed tool (called KC-Viz) organizes the other nodes around the centre (i.e. the node with highest information richness). They evaluated this approach with an empirical experiment: 21 subjects were asked to answer questions (i.e. problem-solving task) using KC-Viz and also OWLViz (the default visualization tool of Protégé). They found out that efficiency of performance was higher for KCViz (i.e. time taken to complete the task was shorter on average). From a subjective evaluation point of view, subjects were asked to report their satisfaction levels as well. Motta et al. showed that KC-Viz led to higher satisfaction among users.

The summary analysis of this method would be similar to Table 1, except for one addition: the data is encoded based on information richness.

Figure 5 shows an example of an ontology in KC-Viz.

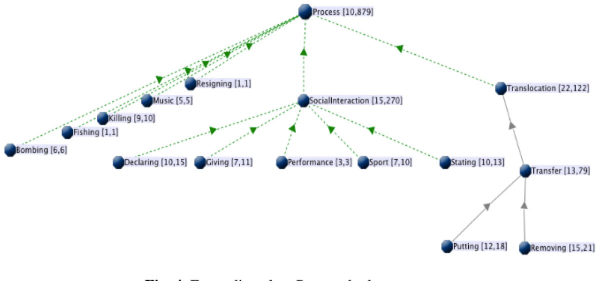

Figure 5. KC-Viz

3.1.4 Wheel-Graph

To visualize content within an ontology (based on user-defined filters), Tscherrig et al. (2012) proposed wheel-graph visualization. Rather than visualizing the whole ontology, they assumed that users are searching for particular information. From the ontology, one can infer what relationships exist, and what relationships can happen (i.e. axioms); thus, based on the axioms, this paper tries to visualize the relationship between search criteria. The authors developed a prototype called Memoria-Mea project. Memoria-Mea creates wheel graphs for each search criterion, and based on the relationship between different criteria, visually structures results of each parameter within a layer.

As an example, they explored an ontology related to travelling. Some of the relevant concepts (classes) in this ontology are: "country", "people", "geographical location", and "activity". The relationships between these classes (i.e. the axioms) are: "people" visit "countries", "people" go to a "geographical location" within a "country", and "people" do some type of "activity" at a "geographical location". Based on these assumptions, when a user searches for the activities done by people who visited Switzerland, Memoria-Mea will generate a layered wheel graph visualization of the results similar to Figure 6.

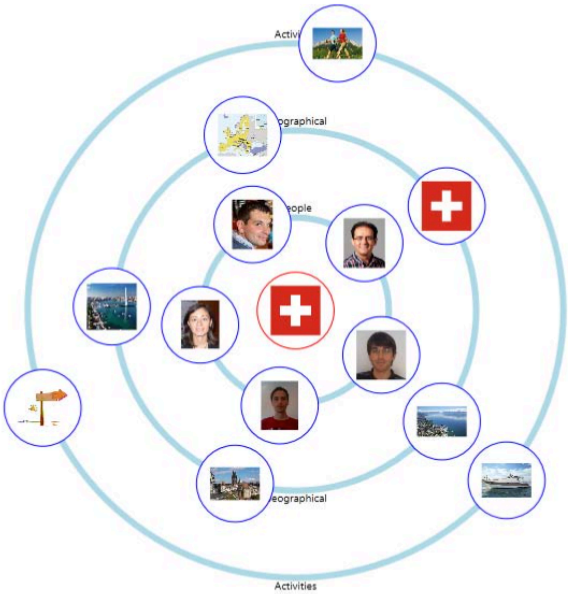

Figure 6. Wheel Graph visualization of content in an ontology

The authors also did a usability study with six subjects. All subjects found the required information using Memoria-Mea (i.e. successful performance of a task). Tscherrig et al. (2012) also evaluated[5] users' subjective perceptions of the visualization; overall subjects found the interface to be easy to use, and "not frustrating". Table 2 summarizes this method:

Table 2. Wheel-Graphs Summary

Idiom	Wheel-graphs
What: Data	Ontological axioms as search criteria
How: Encode	Each criterion is modelled as a circle. Adjacency of circles represents relationships between classes.
Why: Task	Visualizing search results
Scale	Limited to 5-10 different criteria

3.2 Multi-Method Visualization Techniques

3.2.1 Graphs and Space-filling Blocks

In order to improve understandability of OWL ontologies, Jurcik and Sochor (2012) introduced a plug-in for Protégé, called Knoocks. In this visualization method, each node in the graph is a space-filling block that represents class hierarchies. A block is designated for each subclass of OWL:Thing. The subclasses of the said class will be represented in a hierarchy. In the example from Figure 7, "Destination" is a subclass of OWL:Thing. Some of the subclasses of "Destination" are "Country", "Town", and "City".

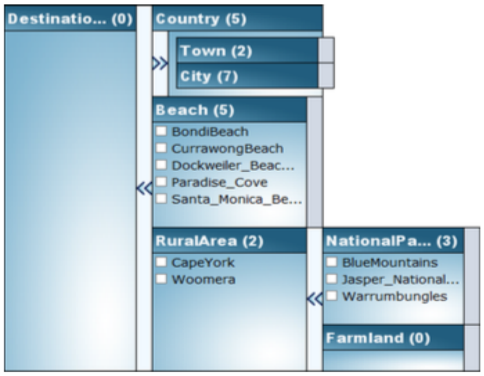

Figure 7. A block in Knoocks

This visualization method is particularly useful for displaying an overview of the whole ontology, in order to achieve a general understandability. As can be seen in Figure 8, the relationships between blocks are visualized as edges between the blocks. Different colours represent different types of relationships. For example, pink is used to model the relationship titled "Travels to", and connects "Passenger" and "Destination" blocks. Table 3 is the summary analysis of this technique:

Table 3. Knoocks Summary

Idiom	Knoocks
What: Data	Ontological data
How: Encode	Class hierarchies are represented as space-filling blocks. To model the relationship between different class hierarchies within the ontology, each block acts as a node in a graph. Links represent relationships between different classes.
Why: Task	Understanding and overview of the ontology
Scale	Limited to 5-10 different criteria

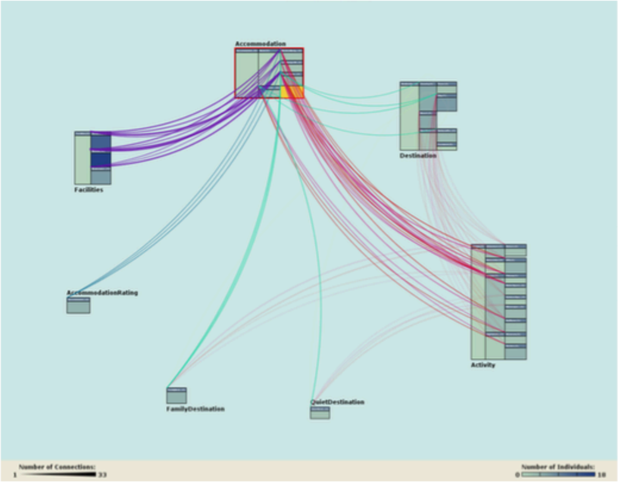

Figure 8. Overview of an ontology in Knoocks

3.2.2 Lists and Linked Histograms

As a design study paper, Streicher and Roller (2012) presented a visualization to display semantic search results. The application domain was image interpretation, for tasks such as pollution detection, cartography, ice layer monitoring and surveillance. These tasks are done on data gathered by Synthetic Aperture Radar (SAR) sensors, and then stored based on "a domain ontology that encompasses concepts of the specific field of work" (Streicher and Roller 2012, p. 51). Their motivations for using ontologies were the facilities that ontologies provide in interoperability (of different data sources), as well as the advantages in performing semantic searches.

The proposed visualization is composed of two views: First view presents a list of the facilities for which SAR data has been gathered. The ranking of this list could be based on the frequency of classes of data for each facility. The second view, which is linked to each of the facilities in the list, presents histograms of signal strengths of different classes of sensory data. The visualization proposed in this study, also allows for inverse lookup of locations based on a special class of sensory data. More specifically, the first view displays classes of sensory data based on location, while the second mechanism, lists locations in which a certain class of sensory data are present. Figures 9 and 10 represent the two features respectively.

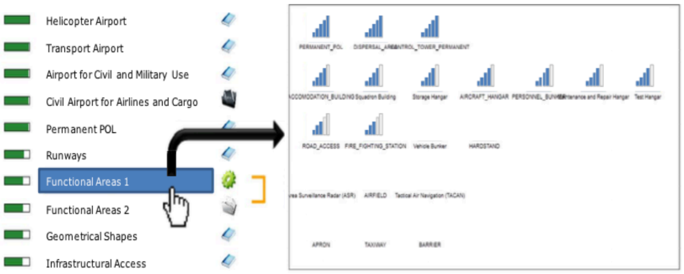

Figure 9. Displaying histograms based on a location on the list

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[5] Descriptive statistics were not provided for this study.

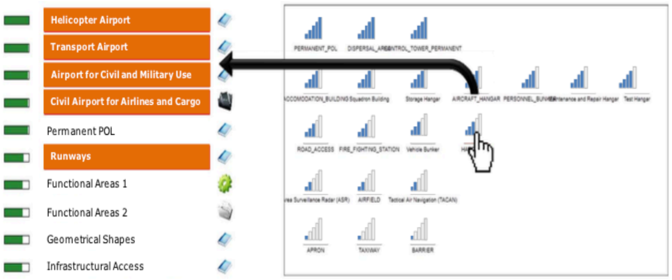


Figure 10. Displaying locations that feature a certain class of sensory data

Table 4 provides a summary of this approach:

Table 4. SAR Summary

Idiom	SAR Visualization
What: Data	Sensory radar ontologies
How: Encode	A list of locations (sorted by frequency) is linked to histograms displaying strength of different signals
Why: Task	Semantic interpretation of sensory data
Scale	Limited

3.2.3 Hierarchical Connected Circles (Radial Layout), Indented Trees, Node-link Diagrams

In order to support seven high-level tasks of overview, zoom, filter, details-on-demand, relate, history, and extract, Kuhar and Podgorelec (2012) proposed a visualization tool that provided multiple views of large and complex ontologies (i.e. high scale). The implementation that they proposed, displays hierarchical connected circles (to provide overview), indented trees (to relate different concepts), and node-link diagrams (for filtering and details-on-demand). They also designed a toolbar through which the user could change the speed of animation for a dynamic graph (showing history of ontology's evolution), and also choose the level of semantic zoom.

Figure 11 shows hierarchical connected circles; the outermost circle shows the top level classes in the ontology (direct children of OWL:Thing). Each of these classes is coded with a colour (different hues). Subclasses of the aforementioned classes are visualized within inner circles, coded with different levels of saturation of the parent's colour. The relationship between classes are also modelled as links, connecting different segments of circles to each other.

Figure 11. Visualizing ontology as hierarchical connected circles

Figure 12 shows a small section of the circle, in which the user has zoomed in to see the information related to the class of "Professor" in more detail.

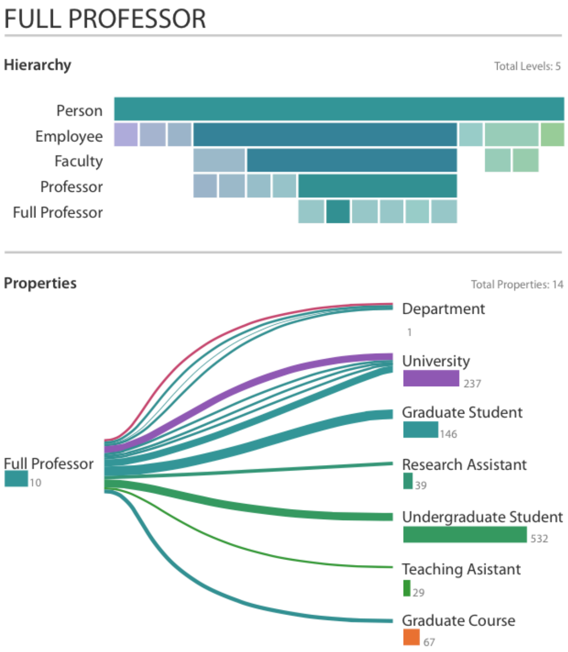


Figure 12. Semantic zoom on one of the classes in the ontology.

Figure 13 shows to toolbox available for filtering, zooming, and animation. Figure 14 displays the indented tree and node-link diagrams of the same ontology.

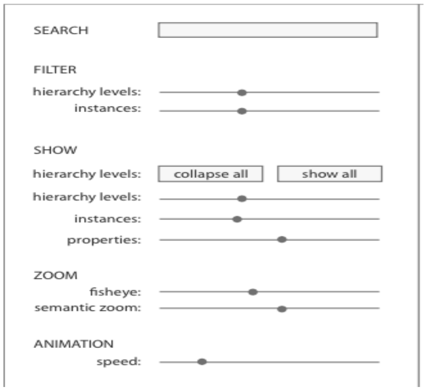


Figure 13. Filtering, zooming, and animation pane

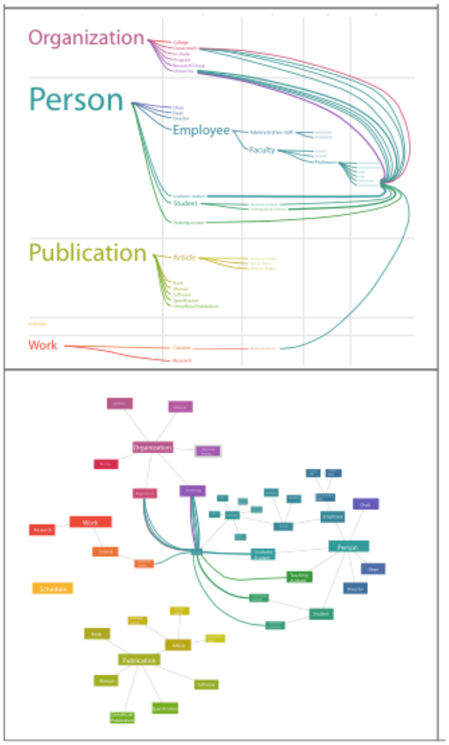


Figure 14. Indented tree and node link visualization of the university ontology

Table 5 summarizes this approach:

Table 5. Multi-View Ontology Visualization Summary

Idiom	Multi-view Ontology Visualization
What: Data	Ontologies
How: Encode	Colour coded hierarchical connected circles represent classes and relationships; indented trees used to zoom on a particular subset of the ontology; and node-link diagrams representing connections between classes
Why: Task	Overview, zoom, filter, details-on-demand, relate, history, and extract
Scale	High

Another (somehow similar) tool was developed by Ma et al. (2012) as part of a design study that visualized geological time-scale data. They also used radial layout (or hierarchical circles) with colour coding, however, they placed the superclasses in the inner circles, while the subclasses were represented in the outer circles (as opposed to the visualization proposed by Kuhar and Podgorelec 2012). Figure 15 shows a snapshot of this tool.

Ma et al. (2012) also did a user study with 19 participants. They asked the users to navigate through the visualization and at the end answer a usability survey. Subjects' average scores were between "useful" and "very useful".

Figure 15. Radial layout to visualize geological data

3.2.4 Hyperbolic and Radial Trees

Another technique proposed to facilitate comprehension of the overall view of the ontology (i.e. concepts and their relationships) is implemented in OntoViewer – a tool developed by da Silva et al. (2012a). This tool facilitates visual exploration of large ontologies by employing three integrated views: "a hyperbolic tree for representing the ontology hierarchy; a classic tree view for showing ontology entities, and an augmented radial tree for displaying relationships between classes" (da Silva et al. 2012, p. 93). The tree view is similar to the indented list that is provided by Protégé (Figure 1). The 2D hyperbolic tree provides focus+context features and reduces the cognitive load of users when interacting with a large ontology. The hyperbolic trees that this paper suggests is similar to force-directed graphs (in Figure 3) that others had also proposed (Mutton and Golbeck 2003; Vercruysse et al. 2012).

The most interesting visualization in OntoViewer is the 2.5D radial tree – which is to some extent similar to hierarchical connected circles (proposed by Kuhar and Podgorelec 2012). The class hierarchy is modelled in the radial tree: the class under focus will be at the centre, and all of its subclasses will orbit (or circle) around it. The relationships between classes (i.e. mutual properties between two classes) are "represented as curved lines in space (thus yielding 2.5D), connecting the related classes without interfering with the display of the hierarchical structure" (da Silva et al. 2012a, p. 93). The tool also allows for viewing the ontology "by choosing to display one or more relationships at the same time or hiding them, choosing which levels of the tree are to be shown or hidden, performing rotations around the axes X, Y and Z, zoom and pan, i.e. providing full 3D navigation" (p. 93). Figure 16 shows the 2.5 radial tree visualization.

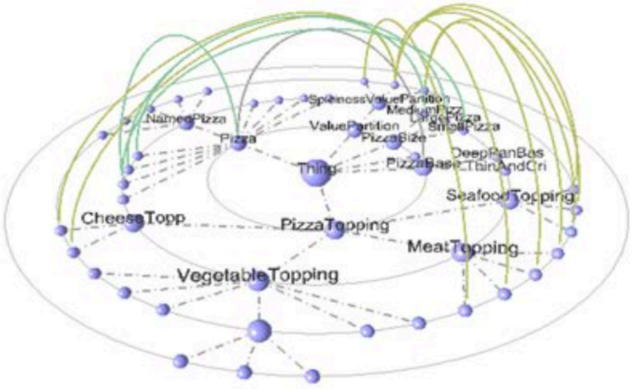


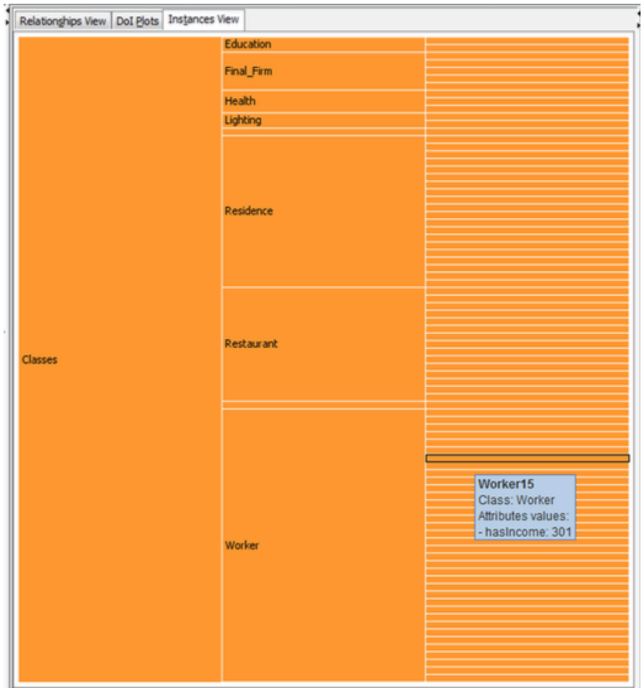
Figure 16. 2.5D Radial Tree Visualization of an ontology

The authors posit that providing multiple and coordinated views in OntoViewer will help in pattern recognition and revealing hidden relationships in large ontologies.

In a later paper, same authors (da Silva et al. 2012b) discuss the possibility of visualizing ontologies using OntoViewer at intensional as well as extensional levels. Intensional level representation deals with classes and relationships between classes (i.e. data schema), while extensional level represents individual observations or instances of classes with specific property values. The authors point out that intensional level is more important from the point of view of knowledge engineers as they may "want to visualize different aspects due to specific demands that arise in certain stages of development, for example, checking the range of an object property" (p. 2). Extensional representations, on the other hand, are claimed to be "more interesting from the point of view of professionals that maintain knowledge databases [since] it seems necessary to have views of the synthetic instances distribution allowing to see how attribute values are distributed and to perform quick visual queries about instances, observing trend in values" (da Silva et al. 2012b, p.2).

The features of OntoViewer introduced earlier enables all the needs of knowledge engineers for viewing intensional level representation of ontologies. As for extensional representation, the authors built upon the OntoViewer tool, and added another view by employing overview+detail methods using an icicle tree. Figure 17 shows an icicle tree representing the instances of the "Worker" class. This visualization is similar to the space-filling blocks in Knoocks (Jurcik and Sochor 2012).

Aggregating the summary analyses in Tables 3 and 5 will describe OntoViewer.



Worker15
Class: Worker
Attributes values:
- hasIncome: 301

Figure 17. Icicle tree from OntoViewer for visualizing ontologies at extensional level

The OntoViewer tool also provides a hybrid view (intensional and extensional), as depicted in Figure 18. The authors also evaluated their tool by interviewing small group of experts – all of whom found the tool "effective".

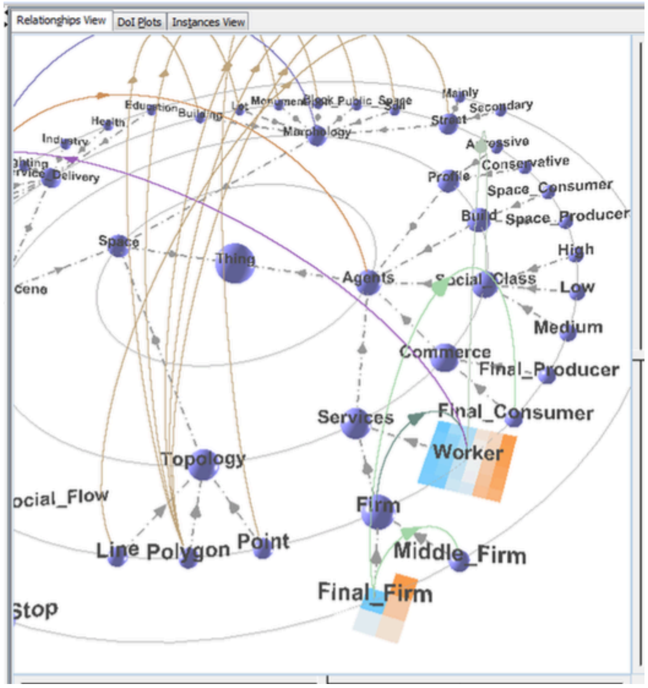


Figure 18. Intensional and extensional representation of an ontology in OntoViewer

3.2.5 Treemap, Hiearchies, and Radial Layout

Another multi-method tool is Onto-VisMod by Garcia-Penalvo et al. (2012) that incorporates treemaps to represent large ontologies (which "uses the whole available space in the dimensional plane"), hierarchical trees to analyse the taxonomy of concepts, and radial layouts to represent the global coupling of an ontology.

The treemaps and hierarchies can be transposed onto each other to give a taxonomy of the domain, while making use of "two-dimensionally squared maps, where the lower levels are represented as internal squares located inside the higher level maps" (p. 11472). Figure 19 captures a snapshot of this view.

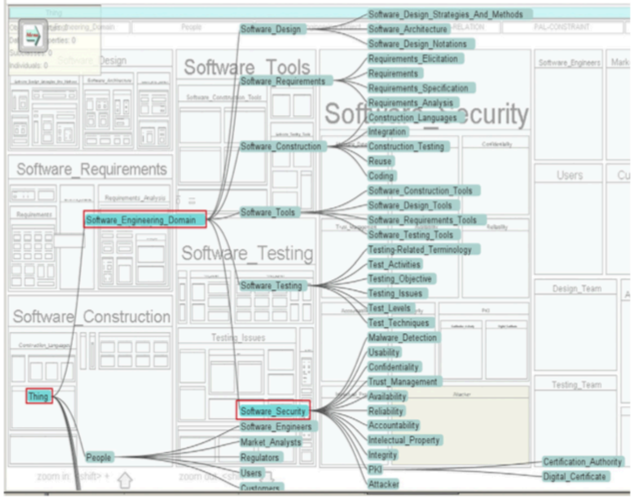


Figure 19. Treemap and hiearchies within an ontology

Onto-VisMod uses radial layouts[6] to visualize the relations among classes in the ontology. On one side of the circle is a list of classes, the other side list of properties. Properties that are used in definition of a class are linked to it.

User has the ability to focus on a particular class: when a class is selected, properties that define it will be highlighted, and the links become coloured. This visualization method is different from hierarchical connected circles (Kuhar and Podgorelec 2012), as the hierarchy of classes is not modelled here, and in addition, the user would see the list of all properties in the relevant universe (i.e. application domain). Figure 20 shows the radial layout view in Onto-VisMod.

The authors did an empirical evaluation of this tool with 21 subjects. The experimental task involved navigation through the ontology and creating a new class. The same task was also done by the users with Protégé. The results of the experiment showed no statistically significant difference in performance (i.e. completion of the task). However, users' satisfaction scores with Onto-VisMod were higher (than their satisfaction with Protégé).

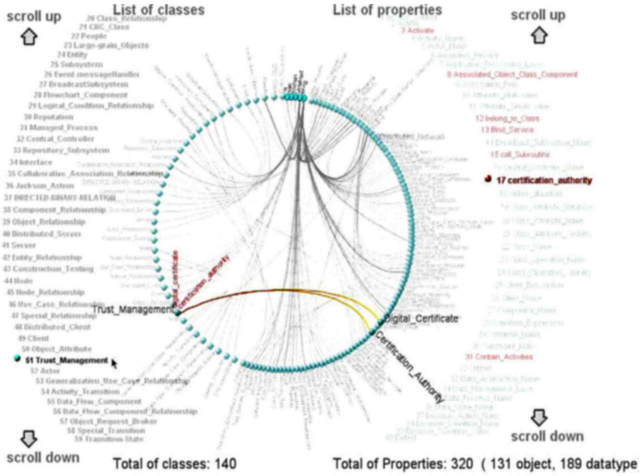


Figure 20. Radial layouts in Onto-VisMod

Table 6 provides a summary of Onto-VisMod

Table 6. Onto-VisMod Summary

Idiom	Onto-VisMod
What: Data	Ontologies
How: Encode	Treemap and hierarchies to represent the class structure. Radial layouts visualize classes and properties. Classes are connected to the properties that define them.
Why: Task	Overview – domain comprehension
Scale	High

3.3 Euler Diagrams

ConceptViz is a tool developed by Burton et al. (2014) that employs Euler diagrams to visualize topological properties of ontologies and provide an overview of the semantic information that an ontology conveys. This approach might be limited in scale, as it only shows the relationships between a few concepts (classes) at a time. However, this method could visually represent set inclusion when a curve is contained by another – reflecting a subsumption relationship. In short, this method is most useful for providing an abstract description of the ontology. Figure 21 shows an example in ConceptVis. Visualizing three concepts in the "Pizza" ontology, it shows that the class of thin and crispy pizzas is a subset of specialty pizzas. At the same time, one can infer that deep pan pizzas and thin and crispy pizzas are disjoint concepts, however, some deep pan pizzas are considered specialties of the pizzeria.

Table 7 summarizes this method.

Table 7. ConceptViz Summary

Idiom	ConceptViz
What: Data	Ontologies
How: Encode	Classes as circles – same principles as Venn diagrams
Why: Task	Overview
Scale	Limited

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[6] This visualization method is different from hierarchical connected circles (Kuhar and Podgorelec 2012), as the hierarchy of classes is not modelled here, and in addition, the user would see the list of all properties in the relevant universe (i.e. application domain).

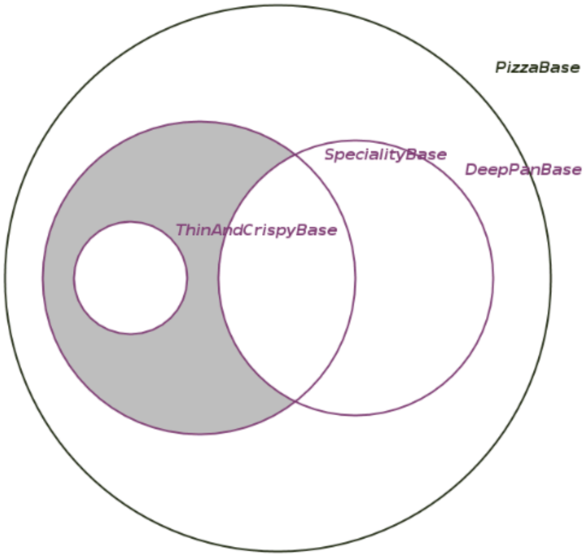


Figure 21. Euler diagram visualization of the pizza ontology

Using Euler diagram visualization of ontologies, Howse et al. (2011) did a case study, and visualized Semantic Sensor Networks (SSN) ontology. SSN is an ontology in the philosophical sense (i.e. structure and order of reality in a broad sense) rather than representation of a single domain. SSN was developed by the World Wide Web Consortium (W3C)[7]; in this ontology world is made of objects that sense, and make observations. Using Euler diagrams, Howse et al. (2011) demonstrate how they can merge simple axioms into more complex axioms to describe the world according to SSN.

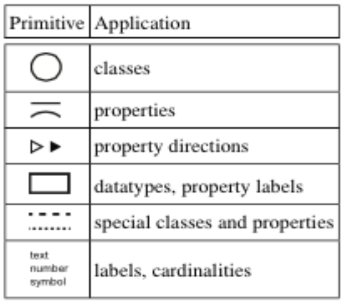
4 METHODS TO MODEL ONTOLOGIES

Significant focus has been put on modelling ontologies in the literature. Here, three of those studies will be briefly discussed.

Silva-Lopez et al. (2014), introduced a graphical notation – called Onto Design Graphics (ODG) – based on UML components. They posit that it could be a standard notation for ontology engineering research; it is easy to learn and could be an efficient method in design and integration of ontologies. The contribution of this work was establishing a formalized mapping between ontological concepts and UML constructs.

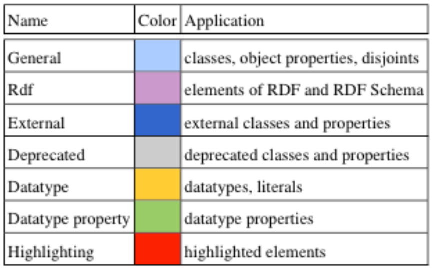
Console et al. (2014) proposed another modelling grammar – named Graphol - as an alternative to UML-based visualization of ontologies. In Graphol grammar, symbolic constructs are assigned to each ontological concept; for example, rectangle for a concept nodes (i.e. class), circle for attributes, and hexagon for individuals (i.e. instances) in the ontology. They performed a an empirical evaluation of Graphol (by comparing with UML-based visualizations); the average correctness scores in comprehension tasks were not statistically[8] different between the two groups (Graphol vs. UML-based), however, users reported Graphol to be easier to use than other methods - This user study was basically a comparison between two graph-based models.

Visual Web Ontology Language (VOWL), is a noteworthy method, which is developed by Lohman et al. (2014). The constructs of this grammar are primitive shapes and a colour scheme (shown in Figures 22 and 23 respectively).



Primitive	Application
○	classes
⌒	properties
▷ ▶	property directions
▭	datatypes, property labels
- - -	special classes and properties
text number symbol	labels, cardinalities

Figure 22. VOWL graphical primitives



Name	Color	Application
General	🟦	classes, object properties, disjoints
Rdf	🟪	elements of RDF and RDF Schema
External	🟦	external classes and properties
Deprecated	⬜	deprecated classes and properties
Datatype	🟨	datatypes, literals
Datatype property	🟩	datatype properties
Highlighting	🟥	highlighted elements

Figure 23. VOWL colour scheme

A user study with six expert users was conducted to evaluate VOWL. The experimental tasks were comprehension questions, and overall, “participants could solve most of the tasks correctly (84%)” (Lohmann et al. 2014, p. 11). This was, however, a qualitative user study in order to verify the general ideas of VOWL, and also receive feedback from users in order to enhance VOWL for non-expert (novice) ontology users.

Figure 24 shows a visualized ontology created with VOWL. Table 8 summarizes the VOWL method.

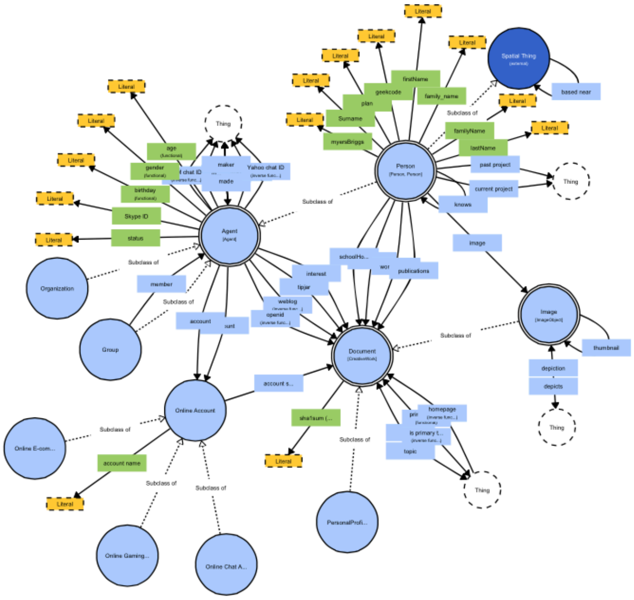


Figure 24. An ontology in VOWL

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[7] http://www.w3.org/2005/Incubator/ssn/ssnx/ssn accessed on 05/12/2014

[8] The authors did not provide descriptive statistics of their tests.

Table 8. VOWL Summary

Idiom	VOWL
What: Data	Ontologies
How: Encode	Primitive shapes, in addition to colours. Zoom and focus features facilitate achievement of users' objectives
Why: Task	Domain Comprehension
Scale	Relatively high

5 META-ANALYSIS

Among the papers that were reviewed in this survey, 11 of them had done a user study. Some of them were qualitative user studies with limited number of participants. However, four of these studies are relatively similar as they study one form of visualization enhancement and compare it with the baseline view of Protégé.

To perform a quantitative review of these studies, a statistical synthesis (i.e. meta-analysis) of their findings was conducted; such analysis enables reflection upon the findings of the past researchers (Borenstein et al. 2011).

A meta-analysis could be conceptualized as either a fixed-effects model or random-effects (Borenstein et al. 2011). Fixed-effects model assumes that all the studies in the meta-analysis are identical and they share a common effect size. Any variation that exists between the findings of different studies in the pool would be due to sampling error. "Put another way, all factors that could influence the effect size are the same in all the studies" (Borenstein et al. 2011, p. 63).

The random-effects model, on the other hand, incorporates a group of studies in a meta-analysis, assuming that they have "enough in common that it makes sense to synthesize the information, but there is generally no reason to assume that they are identical" (Borenstein et al. 2011, p. 69). The variation in different studies is attributed to sampling error, as well as Random Effects Variable (i.e. the variation between studies, such as the chosen variables for the study, or the experimental methods).

The four studies that were analysed here had different independent and dependent variables, yet they all had focused on the impact of visualization on some measure of user performance. Due to the fact that studies in the pool are not identical, random-effects model was chosen for the purpose of this analysis.

5.1 Data Coding

The statistics available from these studies were in the form of means and standard deviations. Therefore, to perform the synthesis (i.e. meta-analysis), the findings of the studies were converted to Cohen's d.

Since the sample sizes were different in each study, Cohen's d-values needed to be unbiased; this was done by assigning weights to the d-values according to their respective standard errors (Borenstein et al. 2011). Positive effect sizes mean that visualization enhancement led to an improvement in performance (e.g. faster completion time, or higher comprehension score) – and vice versa for negative effect sizes. Table 9 represents the data in the analysis.

Table 9. Meta-analysis data

Reference	**Independent Variable**	**Dependent Variable**	**Sample Size**	**Effect Size (Unbiased Cohen's d)**
Katifori et al. 2006	TGViz (Node-link) vs. Protégé	Accuracy	23	-0.49
Motta et al. 2011	KCViz (Node-link) vs. Protégé	Completion Time	21	1.01
		Usability Score	21	0.26
Garcia-Penalvo et al. 2012	OWL-VisMod (tree + radial layout) vs. Protégé	Accuracy	21	-0.14
		Usability Score	21	0.79
Fu et al. 2014	Node-link vs. Protégé	Completion Time	36	-1.32
		Accuracy	36	0

5.2 Analysis and Discussion of Results

The average unbiased Cohen's d of this analysis is 0.014, with the 95% confidence interval of -1.21 to 1.22. This means that an alternative visualization (compared to indented lists in Protégé) can improve a measure of performance by 0.014 standard deviations from the mean (i.e. the average performance achieved by users of indented lists) – which is a very weak effect (almost none). 95% of the time, the impact of the alternative visualization falls in the reported credibility interval. In other words, 95% of the time, an alternative visualization method could reduce performance effectiveness by -1.21 standard deviations or improves it by 1.22 standard deviations.

Grouping the effect sizes based on dependent variables provides additional insights, as seen in Table 10. Accuracy and completion time for users of the baseline representation (i.e. Protégé) is superior to the performance of users when they use alternative visualization methods. However, subjects' perceptions (usability score and satisfaction) will be higher when they have access to alternative visualization methods. The usability score has 95% confidence interval of 0.20 to 0.84, meaning that users will find (mostly graph-based) alternatives more appealing.

Table 10. Grouping the variables of the meta-analysis

Dependent Variable	**Average Unbiased Cohen's d**	**No. of Reported Effect Sizes**	**95% Credibility Interval**
Accuracy	-0.21	3	-0.45 to 0.12
Completion Time	-0.16	2	-2.90 to 2.56
Usability Score	0.53	2	0.20 to 0.84

As possible justification for these findings, one could (tentatively) hypothesize that subjects' perceptions of an alternative visualization method might be influenced by its novelty and differentiation compared to the baseline representation (i.e. indented lists in Protégé); thus, positive impressions lead to higher usability scores for alternative visualization methods. However, as the meta-analysis shows, objective measures - accuracy in particular - are usually higher when users access the indented list representations. This could be due to nature of ontological data, in which hierarchies are inherent to them. Indented lists incorporate the hierarchy, and also are familiar representations to users of computer systems (as used in Windows Explorer, Mac OSX Finder).

6 SUMMARY AND CONCLUSIONS

The present work gathered 21 different studies that had focused on visualization of ontological data. This pool included a mixture of method and design study papers. Each paper was described, and categorized based on its respective visualization method.

Moreover, a meta-analysis was done on four papers that even though they were not identical, they had enough in common to justify synthesizing their findings. These studies had compared alternative visualization methods (three of them studied graph-based visualizations) with the baseline representation of ontologies, which is indented list in Protégé. The analysis shows that measures of accuracy and task completion time are prevailing for baseline visualization (i.e. Protégé) compared to alternative visualization methods. However, subjects find new approaches more satisfying – perhaps due to their novelties.

The present study calls for more effective visualization methods that incorporate the hierarchical nature of data (which are inherent in ontologies); the new methods need to focus on improving objective measures of user performance such as accuracy of answers and task completion time.

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