Developing Non-Empirical Metrics and Tools for Ontology Visualizations Evaluation and Comparing

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<u>Abstract</u>

There are numerous ontology visualization systems, however, the choice of a visualization system is non-trivial, as there is no method for evaluation and comparing them, except for empirical experiments, that are subjective and costly. In this research, we aim to develop non- empirical metrics for ontology visualizations evaluation and comparing. First, we propose several half-formal metrics that require expert evaluation. These metrics are completeness, semanticity, and conservativeness. We apply the proposed metrics to evaluate and compare VOWL, Graphol and Logic Graphs visualization systems. And second, we develop a completely computable measure for the complexity of ontology visualizations, based on graph theory and information theory. In particular, ontology visualizations are considered as hypergraphs and the information measure is derived from the Hartley function. The usage of the proposed information measure is exemplified by the evaluation of visualizations of the sample of axioms from the DoCO ontology in Logic Graphs and Graphol. These results can be practically applied for choosing ontology visualization systems in general and regarding a particular ontology. The application for ontology visualization evaluation and comparing based on the formal metrics is provided.

Keywords: Ontology Visualization, Expert Evaluation, Hypergraphs, Information Measure.

1. Introduction

Visualization of an ontology improves comprehension of knowledge it contains. There are numerous ontology visualization systems, the reviews are presented in [1-3]. However, the choice of a visualization system is non-trivial, as there is no method for evaluation and comparing of ontology visualization systems present in the literature, except for empirical experiments, that are subjective and costly.

Therefore, we aim to develop formal metrics for ontology visualizations estimation. 'Formal' means that they must be objective and computable. Some metrics we propose require external knowledge of the language being visualized, its semantics, and knowledge of other visualization systems, therefore, they are half-formal and require expert evaluation.

Another criterion we propose is based on graph theory and information theory and is fully computable. The intended information measure should estimate not the content of the ontology, as it is the same for each visualization, but the complexity of its form. It implies the following requirements for the intended information measure:

• as it should estimate the complexity of an ontology visualization, it should depend on the complexity of its structure, in other words, on the number of nodes, edges, and types of edges;

- it should be normalized, as visualizations of the same ontology in different visualization systems can have a different number of nodes and edges;
- as it should measure the visualization complexity, a visualization with a greater number of nodes, edges, or edges types should have a higher value of the measure.

The outline of the paper is as follows: in the next section we consider related works, in Section 3 we propose several metrics for expert evaluation, in Section 4 we derive the information measure for ontology visualizations complexity, and finally Section 5 contains the description of the developed application for ontology visualization evaluation and comparing.

2. Related works

A rather small number of works are devoted to the assessment of ontology visualization systems in general. However, as ontology visualization results in a graph, works on graph visualization are also relevant. In [4] the authors propose some recommendations considering graph diagrams, like minimization of crossings between edges. The authors of [5] present empirical research on applying these criteria to automatic graph layout algorithms. In [6] several new shape-based metrics are proposed for large graphs. All these metrics are based on empirical experiments, i.e. on human assessments.

In [7] a metric for graphs with known clustering is described. The authors propose to cluster the nodes in the graph image and to use an existing measure of similarity to compare this clustering and the ground truth one. Unfortunately, ground truth is often not known in the case of ontologies.

$$I(G, \alpha) = |X| \log|X| - \sum_{i=1}^{k} |X_i| \log(|X_i|),$$
(1)

where *G* is a graph, *X* represents a graph invariant and α is an equivalence relation which partitions *X* into *k* subsets *X_i*.

The authors of [9] perform information-theoretic analysis of edge bundling visualizations in terms of adjacency matrices and mutual information. The main idea is that the mutual information between the visual description *O* and the raw data *U* should be maximized

$$I(U,0) = H(U) - H(U|0),$$
(2)

where H(U) is the entropy of U and H(U|O) is the conditional entropy of U given O. But none of the measures presented there satisfy our requirement. Therefore, we develop a new graph information measure.

3. Expert evaluation

First, we propose to consider several features of visualization systems that, though related to the formal properties, like completeness, still require expert evaluation, as they involve external knowledge.

3.1. Completeness

The most important property of a visualization system is its completeness with respect to the language being visualized, because if a visualization system can not represent some axioms of an ontology, the system can not be applied to the ontology. In addition, a common reference language serves as a common denominator for comparing different visualization systems.

Ontologies are denoted on the OWL language [10]. The OWL 1 standard provided three increasingly expressive sub-languages: OWL Lite, OWL DL, and OWL Full. In this paper, we consider OWL DL language, as it provides the maximum expressiveness, retaining decidability.

The formal foundation of OWL is description logics (DLs) [11]. DLs are a family of logic languages, that can be used to represent the terminological knowledge of an application domain. We consider axioms, formulated with the SHOIN description logic syntax, as it corresponds to OWL DL language. We evaluate completeness of a visualization system by counting the number of SHOIN syntax entities that the system can represent.

3.2. Semanticity

We suppose, the advantage of a visualization with respect to a reference language is that it improves comprehension of a formula with representing its semantic. Therefore, we propose to evaluate the ability of a visualization system to represent semantics of expressions. We consider a diagram of a visualization system for a logical relation as semantical, if it represents the semantic of the relation. For example, compare the visualization of conjunction from Graphol [12], Fig. 1, with the corresponding Venn diagram [13], Fig. 2. Venn diagram represents that these two sets have common elements, while in Graphol conjunction is just labeled with a hexagon.



Fig.1. Conjunction in Graphol



Fig.2. Conjunction in Venn diagrams

3.3. Conservativeness

Finally, we suppose that it is important to use existing graphic primitives from mathematical theories, as in the other case, i.e. introducing new graphic primitives, instead of helping a user to understand an ontology it forces him or her to learn just one more language. Considering again the example above, in Graphol a user has to learn that hexagon denotes conjunction, while if the Venn diagram was used, the user familiar with Venn diagrams would have understood the diagram without additional instructions. Therefore, we consider a graphic primitive to be conservative if an expert can name an already existing formal system, where it is adopted from.

3.4. Example of evaluation

We provide an evaluation of the VOWL [14], Graphol, and Logic Graphs (LGs) [15] visualization system as examples. We examined its completeness with respect to OWL DL language, its semanticity, the ability to represent the semantics of relations, and whether its graphic primitives are new or adopted from some common visualization systems. See Table 1, Table 2 and Table 3 respectively.

We see that VOWL can represent only 12 of 15 entities of the SHOIN description logic, therefore, its completeness rate is 0.8. The diagrams for concepts, conjunction, disjunction, and equivalence are semantical and conservative, as they are based on the Venn diagrams. The diagram for roles can be considered as graph-theory based, therefore, it is also semantical and conservative. The diagram for negation is conservative, as it uses the sign of negation from logic, but it is not semantical, since it doesn't represent the semantic of negation, i.e. a user wouldn't have distinguished negation from another concept if there wasn't the label of negation on it.

Considering Graphol, it is complete, but there are only arbitrary graphic primitives that would have been indistinguishable if there were no labels. Speaking of labels, Graphol mainly uses natural language names for operations that are understandable for new users and, therefore, conservative.

LGs, the semantically oriented ontology visualization method, developed by us, is complete, mostly semantical and conservative, since it is based on Venn diagrams, graph theory, and

Ch. S. Peirce's existential graphs [16]. We use non-semantical primitives for number restrictions and functional roles as their semantical representations are inconvenient, and non-semantical and non-conservative primitive for concept inclusion due to the strong tradition in ontology visualization.

The resulting scores of the considered visualization systems are presented in Table 4.

4. Information measuring

In the previous section, we proposed several metrics for expert-based evaluation. Properties like completeness and conservativeness are important for visualization systems evaluation, but it ishard to imagine that they would be fully computable. Thus, we propose one more approach to ontology visualization systems evaluation intended to be completely formal. This approach is based on information measuring.

4.1. Hypergraphs as the formal framework

Before defining the information measure, we have to define the formal framework. We propose to consider ontology visualization as a hypergraph. Simple graphs are not suitable for our goals as many ontology visualization systems use edges connecting more than two nodes. A hypergraph can be represented as an incidence matrix, therefore, an ontology visualization can be

N	Entity	Complete	Semantical	Conservative
1	Concept	Coss	1	1
2	Role	Class A Property A Property A Class B	1	1
3	Negation	Class	0	1
4	Conjunction		1	1
5	Disjunction	(Class A) = -((b)) = -(Class B)	1	1
6	Existential restriction		0	0
7	Universal restriction		0	0
8	Transitive role	Class A Class B Class B	0	0
9	Inverse role	Class A ObjectProperty Class B	0	0
10	Role hierarchy	Class A Subproperty Class B	0	0
11	Number restriction	Class A Property X.y Class B	0	0
12	Nominal		0	0
13	Functional role	Class A Property (Inclose) Class B	0	0
14	Concept inclusion	Ciass A Subclass of Ciass B	0	0
15	Concept equivalence	Cana	1	1
		0.8	0.33	0.4

Table 1. Expert-based evaluation of VOWL

Ν	Entity	Complete	Semantical	Conservative
1	Concept	Concept	1	1
2	Role	Role	1	1
3	Negation	(not)	0	1
4	Conjunction	and	0	1
5	Disjunction	or	0	1
6	Existential restriction	exists	0	1
7	Universal restriction	forall	0	1
8	Transitive role		0	0
9	Inverse role		0	0
10	Role hierarchy	Role1 Role2	0	0
11	Number restriction	(-,x)	0	1
12	Nominal	oneOf	0	1
13	Functional role	exists Role	0	0
14	Concept inclusion	Concept1 Concept2	0	0
15	Concept equivalence	Concept1 Concept2	0	0
		1	0.07	0.6

Table 2.Expert-based evaluation of Graphol

Table 3. Expert-based evaluation of LGs

Ν	Entity	Complete	Semantical	Conservative
1	Concept	С	1	1
2	Role		1	1
3	Negation	C	1	1
4	Conjunction		1	1
5	Disjunction		1	1
6	Existential restriction	Domain C	1	1
7	Universal restriction	Domain C	1	1
8	Transitive role		1	1

9	Inverse role		1	1
10	Role hierarchy		1	1
11	Number restriction	C1 C2	0	1
12	Nominal	- 20, 20, 20, 20, 20, 20, 20, 20, 20,	1	1
13	Functional role	CI C2	0	1
14	Concept inclusion	C1 SubClassOf	0	0
15	Concept equivalence		1	1
		1	0.8	0.93

Table 4. Expert-based comparing of VOWL and LG

	Complete	Semantical	Conservative
VOWL	0.8	0.33	0.4
Graphol	1	0.07	0.6
LGs	1	0.8	0.93

represented as an incidence matrix as well.

Let there is a hypergraph H = (X, E), where X - is a set of nodes and E is a set of edges. It is represented with $|X| \times |E|$ incidence matrix $A = (a_{ij})$, where

$$a_{ij} = \begin{cases} 1, if \ x_i \in e_j \\ 0, otherwise \end{cases}$$
(3)

for undirected graph and

$$a_{ij} = \begin{cases} -1, if (x_i, x') \in e_j \\ 1, if (x', x_i) \in e_j \\ 0, otherwise \end{cases}$$
(4)

and

$$a_{ij} = 2 \ if e_j = (x', x_i)$$
 (5)

Consider the following axiom from the Document Components Ontology (DoCO) [17] as the example (6)

chapter $\sqsubseteq \exists$ contains.paragraph \sqcup section

and its visualization in the Graphol system, see Fig. 3. Here edges denoting



Fig. 3. Visualization of the axiom 1 in Graphol

disjunction connect three nodes: 'graphol.paragraph', 'graphol.section' and 'or', therefore, it is the hypergraph. The incidence matrix for this hypergraph is Table 5. Each node of the diagram corresponds to a row of the matrix and each relation - to a column. As nodes

Table 5. The incluence matrix for the axiom 1 in Graphor							
	subClassOf	graphol.contains	or				
exists	1	1	0				
graphol.chapter	1	0	0				
graphol.contains	0	1	0				
graphol.paragraph	0	0	1				
graphol.sections	0	0	1				
or	0	1	1				

'graphol.paragraph', 'graphol.section' and 'or' are connected with the edge 'or', the corresponding cells have value 1. In this research, we ignore the direction of edges for simplicity. Table 5. The incidence matrix for the axiom 1 in Graphol

Definition 1. For a given incidence matrix A the set of all values is {a}.

For undirected graph $\{a\} = \{0,1\}$, for directed $\{a\} = \{-1,0,1\}$, for directed graph with loops $\{a\} = \{-1, 0, 1, 2\}$ and so on.

Now we define the set of all possible edges ε :

Definition 2. For a hypergraph H with a given set of nodes X the set of all possible edges $\varepsilon = \{a\}^X$.

We are ready to define the information measure for hypergraph complexity estimation by deriving it from the Hartley function [18]

$$\log_b |A|$$
 (7)

where *A* is an arbitrary set and *b* – an arbitrary number. We substitute the number of edges |E| as |A| and the number of all possible edges $|\varepsilon|$ as *b*.

Definition 3. For a hypergraph H with a given set of nodes *X*, a given set of edges *E* and a set of corresponding incidence matrix values $\{a\}$, the information I(H) is following:

$$I(H) = \log_{|\varepsilon|} |E| = \frac{1}{|X|} \log_{|\{a\}|} |E|$$
(8)

Consider several simple graphs for illustration, see Fig. 4, its information estimation is at the Table 6. As we see, H_2 has a more complex structure comparing to H1 and, therefore, its information value is higher. H_3 is directed and each directed edge contains less information, therefore, with the same number of edges its information value is lower compared to H_1 . Summing up, the information measure satisfies the desired properties.

Н	X		{ <i>a</i> }	I(H)
1	3	2	2	0.33
2	3	3	2	0.53
3	3	3	3	0.21

Table 6. Information estimation of the graph examples



Fig. 4. The graph examples

4.2. Comparing visualizations with the information measure

We provide an example of comparing ontology visualizations with the developed information measure. Unlike expert-based evaluation, where we compared visualization systems itself, for information measure we have to compare visualizations of a particular ontology. We use the DoCO ontology as it is a real ontology, used in different applications, and it contains nontrivial axioms. We visualized some axioms of this ontology in Graphol and Logic Graphs. The list of axioms and their visualizations are in Table 7.

The example of an incidence matrix for Graphol was provided in Table 5. Now consider the example of the incidence matrix for Logic Graphs. The incidence matrix for the axiom 1 in Logic graphs is Table 8.

We compare LGs with Graphol by measuring information of the correspond- ing visualizations for the sample of axioms, presented in Table 7. We selected the axioms according to the following criteria:

- the axioms must have non-trivial form, i.e. contain more than one operation;
- each axiom must have a unique structure, i.e. none two axioms can have the same combination of operations;
- the sample must contain all types of operations: negation, conjunction, disjunction, inclusion, roles with existential and universal restrictions.

The result is in Table 9. As we see, the average information of LGs on this sample is higher, than of Graphol.

 $chapter \sqsubseteq \exists contains. paragraph \sqcup section$ 1 graphil chapter $abstract \subseteq (chapter \sqcup section) \sqcap (\exists ispart of. body matter \sqcup front matter)$ 2 afterword \sqsubseteq section $\sqcap \exists ispart of. backmatter$ 3 appendix \sqsubseteq (section \sqcap headed container) \sqcap \exists ispart of . backmatter 4 headed container backmatter \sqsubseteq discourse element \sqcap container 5 discourse element and a second sec $chapterlabel \sqsubseteq \neg sectionlabel$ 6 graphol shapter, subttle, _______ not _____ graphol section, lable $chaptersubtitle \sqsubseteq \exists ispart of. chapter$ 7

Table 7. Visualizations of DoCO in LGs and Graphol



Table 8. The incidence matrix for axiom 1 in LGs

	subClassOf	contains	negation 1	negation 2	conjunction	negation 3		
chapter	1	0	0	0	0	0		
conjunction	0	1	0	0	1	1		
domain	1	1	0	0	0	0		
paragraph	0	0	1	0	1	0		
section	0	0	0	1	1	0		

Table 9. Comparing information of ontology visualizations

N	LG			Graphol				
	X	E	{ <i>a</i> }	I(H)	X	E	{ <i>a</i> }	I(H)
1	5	6	2	0.52	6	3	2	0.26
2	9	11	2	0.38	10	5	2	0.23
3	5	3	2	0.32	6	3	2	0.26
4	7	4	2	0.29	8	4	2	0.25
5	4	2	2	0.25	4	2	2	0.25
6	2	2	2	0.5	3	2	2	0.33
7	3	2	2	0.33	4	2	2	0.25
8	4	5	2	0.58	4	2	2	0.25
9	7	7	2	0.4	8	4	2	0.25
10	10	11	2	0.35	12	6	2	0.22
				0.39				0.26

5. Realization

As a part of this research, an application has been implemented. It includes a basic ontology visualization tool, a library of formal ontology visualization metrics, and an algorithm for constructing the best visualization according to the selected metrics.

The application is implemented with JavaFX, for graph representation Graph- stream library [19] is used and ontologies are imported with the help of OWL API [20]. Several decisions have been made in the course of development to improve the readability of ontologies. Firstly, in order to reduce visual clutter, labels of edges are shown only when they hover. Secondly, there is an option on the conversion step to remove nodes with a degree less than the specified threshold. A similar option exists in WebVOWL [21], the rationale behind it is that the most important concepts in an ontology often correspond to nodes with the largest degrees. Screenshots of the application are shown in Fig. 5.

			- 0 😣
File			
Ontology URL	http://xmlns.com/foaf	f/spec/index.rdf	Import
Ontology-to-graph conversion options			
Remove nodes with degree less than	0	×	
Use predefined converter Choose converter automatically	Ontograf	Fotropy	
Layout options	Graph metric	Спатору	
Use predefined algorithm		•	
Choose layout automatically	Layout metric	Number of crossings 🔻	Visualize
Choosing best graph representation with m Value of metric with converter Ontograf: 1. Value of metric with converter OWLViz: 0.9 Chose OWLViz Choosing best layout with metric Number o Average value of metric for LinLog: 5.4 Average value of metric for SpringBox: 0.0 Chose SpringBox	etric Entropy 720 49 f crossings		

Fig. 5. Application menu

The workflow of the application consists of two steps: 1) conversion of an ontology to a graph and 2) constructing the layout for the graph. For both steps, users could either set an algorithm explicitly or let the program choose it automatically based on a selected quality metric. The resulting graph also could be exported to DOT. Data flow in the application is summarized in Fig. 6.



Fig. 6. Data flow in the application

The application includes the library of visualization metrics. For the conversion step, the library includes a special case of the proposed formal metric (8) with $|\{a\}| = 2$. Along with it, there is the graph entropy metric (1) with X being the set of nodes. Two nodes are considered equivalent if they have the same degree. For the layout step, the aesthetic metrics from the field of graph drawing are used, including the number of edge crossings and similarity with shape graph, namely, k-nearest neighbors graph [6].

If a user sets a visualization metric instead of explicit visualization parameters, the application searches for the best visualization algorithm automatically, based on the selected metric. First, the metric is evaluated on the result of each algorithm. Then the algorithm with the best value (the highest or the lowest, depending on the meaning of the metric) of the metric is chosen. Since force-directed algorithms use randomization, they are run multiple times, and the mean value of the metric for all runs is used.

The application provides two ways to evaluate and compare the visualizations produced by other ontology visualization tools. The first way is to simulate the results with the proper algorithms in the application. At the moment, conversion algorithms from visualization tools Ontograf [22] and OWLViz [23] are supported. The second way is to import the result. Some visualization tools, e.g. WebVOWL, support export to DOT, so the application supports import from this format. As per layout, several force-directed algorithms are supported.

As an example, the visualization of the FOAF ontology [24] in the application is provided at Fig. 7.



Fig. 7. Visualization of the FOAF ontology in the application

6. Conclusion

In this research, we proposed several non-empirical metrics for ontology visualization evaluation and comparing. These metrics are divided into two groups. The first group includes three metrics: completeness, semanticity, and conservativeness. These metrics require expert evaluation and, therefore, they are half-formal. As an example, we compared ontology visualization systems: VOWL Graphol and Logic Graphs.

The second group consists of the completely computable information measure, derived from the Hartley formula, that allows normalized measuring complexity of ontology visualizations, represented as hypergraphs with incidence matrices. As an example, we compared Logic Graphs with Graphol by measuring average information of visualizations of the sample of axioms from the DoCO ontology.

These results can be practically applied for choosing ontology visualization systems in general and regarding a particular ontology. Considering the presented examples, it is recommended to use LGs rather than VOWL in general, as it has higher scores of completeness, semanticity, and conservativeness, and for visualizing the mentioned fragment of the DoCO, as LGs has higher informativeness.

As the implementation of the results, the application for ontology visualization evaluation and comparing has been developed. It includes the basic ontology visualization tool, the library of formal ontology visualization metrics, and the algorithm for constructing the optimal visualization according to the selected metrics. The application supports simulation of several ontology visualization tools and import and export to DOT format.

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