A Proposal for an Ontology Metrics Selection Process

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Abstract: Ontologies are the glue for the semantic web, knowledge graphs, and rule-based intelligence in general. They build on description logic, and their development is a non-trivial task. The underlying complexity emphasizes the need for quality control, and one way to measure ontologies is through ontology metrics. For a long time, the calculation of ontology metrics was merely a theoretical proposal: While there was no shortage of proposed ontology metrics, actual applications were mostly missing. That changed with the creation of NEOntometrics, a tool that implemented the majority of ontology metrics proposed in the literature. While it is now possible to calculate large amounts of ontology metrics, it also revealed that the calculation alone does not make the metrics useful (yet). In NEOntometrics alone, there are over 160 ontology metrics – a careful selection for the given use case is crucial. This position paper argues for a selection process for ontology metrics. It first presents core questions for identifying the underlying ontology requirements and then guides users to identify the correct attributes and their associated measures.

1 INTRODUCTION

Ontologies are central to sharing meaning between different human and computational actors. They are at the foundation of the semantic web and knowledge graphs and enable the alignment of different terminologies, to encode business rules or formally describe a domain to the computer. They have the potential to break down data silos and make implicit knowledge explicit through inference machines. Developing ontologies, however, is not a trivial task: The world wide web consortium standardized (w3c) the web ontology language OWL, which builds on description logic. It provides sophisticated features to formalize classes and relations, and mostly, there is not one right way to model a domain, but there are many ways to skin a cat.

The complexity and high degree of freedom puts quality control activities at the forefront. Automatically calculated metrics offer an objective and quick view on ontologies. They show an abstraction of the inner fabrics, which can detect potential irregularities and track the development progress overall (Vrandečić & Sure, 2007).

While the usefulness of ontology metrics is undoubted, the past years had an implementation gap. While many ontology metrics and frameworks were proposed, e.g., by (Gangemi et al., 2006), (Tartir et al., 2005), or (Burton-Jones et al., 2005), for a long time, there was just minimal tool support for bringing these frameworks into use. That changed with the introduction of Ontometrics (Lantow, 2016) and its predecessor, NEOntometrics (Reiz & Sandkuhl, 2022b), which calculates most of the proposed ontology metrics. With these developments, ontology metrics found applications in corporations (Reiz et al., 2020) and research projects (Blagec et al., 2022; Rocha et al., 2020).

With the necessary tools, a new challenge arose: The number of metrics for ontology developers, especially inexperienced ones, is overwhelming. OntoMetrics calculates 81 ontology measures and NEOntometrics over 160. Knowledge engineers need a small subset of key performance indicators (KPIs) that quickly tell the main development aspects for a given ontology. At the same time, ontologies are too heterogenous to derive standard rules on their development, and there are no sets of metrics that are helpful for everybody (Reiz & Sandkuhl, 2022a).

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This position paper argues that metric selection is crucial for bringing ontology metrics into use. One can develop document types like taxonomies, glossaries, or data models that are all legitimately called ontologies and conform to the OWL standard. Their application scenarios, users, and underlying strategy are likely vastly different, and so is the required evaluation. This position paper presents a process for first answering core questions to identify the ontology requirements and then selecting the right metrics.

This contribution is structured as follows: The next section describes the challenges in ontology evaluation and metric selection, section three proposes a methodology for metric selection, followed by a conclusion.

2 SELECTING METRICS: A NON-TRIVIAL TASK

The upcoming section first presents the variety of document types and how they can be modeled with ontology languages. Afterward, the section argues for ontology evaluation using ontology metrics and recapitulates existing metric frameworks. At last, the heterogeneity of ontology development processes motivates the creation of the metric selection process.

2.1 One Ontology, Many Possible Document Types

There is no scientific dispute on the definition of computational ontologies. It is an *"... explicit specification of a conceptualization",* according to the highly cited paper by (Gruber, 1993). The standardizations of these artifacts are also settled with the recommendation for the web ontology language (OWL) and RDF Schema (RDFS)[1] by the world wide web consortium (w3c).

These technologies can cover many different application scenarios. Figure 1 categorizes document types and technologies along a formality scale and according to document categories. OWL and RDFS allow knowledge engineers to develop highly sophisticated interconnected graphs that maximize the inferring of hidden facts. However, building only a rudimentary glossary, a loose collection of words with human-centered annotations that do not incorporate other logical meanings, is also possible.

Both can adhere fully to the standard and can be measured using ontology metrics. As the purpose of the ontologies probably differs widely, it is no use to qualify either as *better* or *worse*. An ontology that is meant to be a *taxonomy* has a different goal than one that shall be a *data model*. Both should not be treated in the same way, and a set of metrics that works for the first ontology will likely not work for the second one.

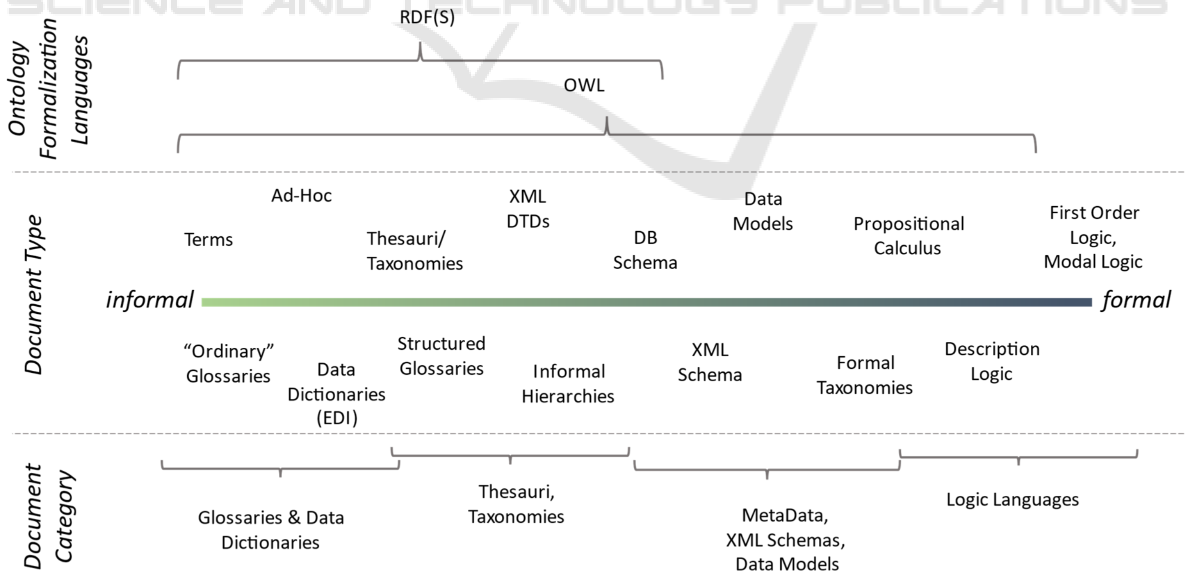

Figure 1: The various document types and their category. Figure adapted and extended from (Uschold & Gruninger, 2004).

[1] https://www.w3.org/TR/owl2-overview/, https://www.w3.org/TR/rdf-schema/

Table 1: Description and formal implications of the document types of Figure 1.

Document Type	Definition/Description	Cumulative Attributes
Terms	Concepts and Relationships.	None.
"Ordinary" Glossary	List of words relating to a specific subject, text, or dialect, with explanations; a brief dictionary.	Further information (e.g., labels).
Ad-Hoc Hierarchy	Extensive, deep hierarchy with links to further resources (Labrou & Finin, 1999).	Adding hierarchy and links.
Data Dictionaries (EDI)	An inventory that specifies the source, location, ownership, usage, and destination of all of the data elements that are stored in a database (Institute for Telecommunication Sciences [ITS], 2001).	Add meta-information, source, and destination of data elements.
Thesaurus	List of related word groups, organized by a combination of attributes. Entries include synonyms. (Cross & Pal, 2005, p. 449).	Equivalent-relations.
Structured Glossary / Directory	Access one piece of information using another. Taxonomic relationships might exist (e.g., is-a). Even though relations exist, its structure is relatively flat.	More expressive relations between entities, basic structure (though not formalized).
XML DTDs	XML Document Type Declaration, defines hierarchical structures including identifiers, attributes, and entities (Hitzler et al., 2008).	Allowing strict structure definition, with basic cardinalities.
Informal Hierarchy (Folksonomy)	The users tag information onto items. An interlinked hierarchy can be created using statistical evaluation.	Interlinked hierarchy.
DB Schema	Formalizing non-typed relations between structured data (Curtis & Cobham, 2008).	Definition of formal relations, data types.
XML Schema	Like DTD, with exact cardinality and data type support, and unique ID keys, reusing schemas is possible through imports (Fallside & Walmsley, 2004).	Exact cardinalities & data types.
Data Models (e.g., UML, step)	A conceptual data model containing typed relations between objects (Curtis & Cobham, 2008).	Typed relations.
Formal Taxonomies	Machine-readable structure with interlinked objects.	Machine-readable links.
Propositional Calculus	Formal algebra, declaration of facts (Lifschitz et al., 2008).	Decidable: Computer can infer if statements are valid.
Description Logic	Formal algebra. Can be viewed as a decidable subset of first-order logic (Baader et al., 2008; Bruijn & Heymans, 2008).	Decidable, enables automatic inference algorithms.
First-Order Logic	Formally based logic algebra with quantifiers and relations. (Bruijn & Heymans, 2008; Lifschitz et al., 2008).	Non-decidable

2.2 Ontology Evaluation Methods and Why to Choose Metrics

(Tankelevičiene & Damaševičius, 2009) collected three definitions for quality in ontologies, namely the *"conformance to requirements"*, *"fitness to* use", and *"the totality of features and characteristics of a software product that bear on its ability to satisfy stated or implied needs"*. As a result, the ontology fulfills a function, and the quality reflects how well it can fulfill this function.

In his state-of-the-art, (Raad & Cruz, 2015) collected the various ontology evaluation methods, namely gold-standard, corpus-, task-, and criteria-based. Gold-standard-based approaches are best suited to evaluate ontology mapping or learning. They compare a created ontology to a reference considered "perfect". Corpus-based evaluations assess the coverage of a given domain by assessing a learned ontology with the content of a text-corpus, while task-based assessments measure an ontology's ability to fulfill a given task, regardless of the structural characteristics. Criteria-based approaches regard the construction of the ontology on structural or complex meta-logical attributes. While the first can be performed automatically, the latter is mainly based on an expert evaluation.

The first two evaluation methods are a good fit for ontology learning but challenging to apply beyond. Likely, an ontology is not modeled according to a text corpus, and a gold standard does not exist. Task-based approaches require the consideration of an application context on which the performance of an ontology is evaluated. Thus, the evaluation methodologies need to be highly customized and are different to scale to a broader audience. Criteria-based approaches build on the inherent structure that every ontology has. Complex approaches that build on meta-logical consistency need the human intervention of skilled knowledge engineers.

Approaches building on measuring structural attributes can be calculated automatically for every ontology regardless of the usage context. That makes it highly scalable and a solution that is easy to implement. However, their influence on the individual notion of quality is not as easy to assess as for the other methodologies, as the attributes are rather abstract, and e.g., do not consider the fitness to fulfill a task. The selection of the proper measures is cumbersome, and the interpretation guidelines of the metric frameworks, if there are any, are highly generalized and possibly not applicable to the use case at hand. Without interpretation, the measures mostly remain arbitrary to the metric consumer.

2.3 The Questionable Promises of too Easy Solutions

The details of the descriptions in the various ontology metric frameworks differ significantly. oQual by (Gangemi et al., 2005) provides only minimal textual guidance. More detailed descriptions and advice for the metric interpretation are offered in OntoQA by (Tartir et al., 2005).

The most holistic approach is proposed by (Duque-Ramos et al., 2011) in the OQuaRE framework. It defines 18 metrics and links these to quality characteristics like *usability* or *adaptability*. It firmly guides the metric interpretation by giving predefined scores from 1 (worst) to 5 (best), depending on the resulting value ranges. However, research has shown that the quality scores fail to capture the reality of modeled ontologies. A study of 4094 ontologies (Reiz & Sandkuhl, 2023) identified that many measures are heavily tilted toward the best or worst grades. For seven of the 18 metrics, more than 80% of the ontologies are at these extreme values. Only five of the measures are somewhat evenly distributed, and none of the metrics show a gaussian curve, even though quality typically follows such a pattern, with only some being best or worst and most being in the middle.

Further research collected empirical evidence for the highly heterogenous development processes of ontologies. In a study by (Reiz & Sandkuhl, 2022a) on the evolutional process of 69 dormant ontologies, the authors found no evidence that these artifacts share standard development processes. Conversely, common assumptions could not be supported, e.g., ontologies get larger and more complex with increasing maturity.

Regarding the selection of ontology metrics, it supports the notion that ontologies are too heterogenous that a simple set of measures can capture the individual requirements of all or the majority of knowledge engineers. Only one framework has claimed this achievement, but with questionable validity. While extensive descriptions of proposed metrics like in OntoQA are still helpful, there is no silver bullet for ontology evaluation, and metrics must be carefully selected and interpreted.

3 SELECTING METRICS FOR QUALITY CONTROL

Ontology metrics measure structural attributes. Quality, however, is highly dependent on one's individual requirements. Before a knowledge engineer can use ontology metrics to assess something similar to quality, it is necessary to match these requirements with attributes used to fulfill the needs and metrics that measure these attributes. Giving a set of requirements alone, e.g., in the form of competency questions, does not tell much about the used or required formalizations, as there are almost countless options to create a model.

If an ontology is created from scratch, and the evaluation is considered from the start, a **top-down** approach can work. Here, the types of used attributes and their formalizations are determined prior to the development of the ontology.

More likely, though, the artifact reuses existing ontologies and already has a development history. In these cases, a **bottom-up** evaluation is better suited. Analyzing the existing ontology and its structure, one tries to derive the attributes that best capture its developments.

Questioning the goal of the ontology and the evaluation can aid the top-down and bottom-up approaches. Some core questions are depicted in Table 2, but given the individual circumstances, this list might be non-exhaustive. With these considerations, one can identify and map the required attributes to corresponding ontology metrics.

3.1 Initiating a Top-down Metric-Driven Ontology Development

The long-term **strategy** is the first thing to consider at the beginning of a new ontology development process. Is there just one imminent use, also for the long term? Alternatively, should other goals, like the alignment with other ontologies or applications, be considered? If that is the case, these design decisions should be undertaken at the very beginning, e.g., by analyzing the future requirements and the ontologies that need to be integrated. If strategic goals exist, e.g., for using specific constructs, these attributes can be selected early on.

Table 2: Core questions for metric selection.

Q	Question	Identify…
1	What is the long-term **strategic** goal?	future integrations
2	**What** is modeled?	the document category
3	Which **applications** use the ontology?	how and where the ontology is used
4	**How** is it modeled?	the used formalizations
5	Who is the **consumer?**	the required information for the stakeholders

The second question regards **what** kind of document category and type the ontology should have. Here, Table 1 provides support in categorizing the possible varieties. The used attributes in an ontology depend on the kind of document modeled (cf. Figure 2).

Q3 considers the **application** landscape. The applications likely have requirements regarding the functionality, data structures, and interfaces that the ontology needs to provide. These constructs can be mapped to the underlying attributes to track whether the required constructs are being built.

Now, more concrete planning can begin, and the question of **how** to model the actual ontology arises. The first three questions identified many requirements and attributes that can be used for the given purposes. However, there are many ways to instantiate the model. This step will probably disregard some of the previous considerations and attributes. At the end of working on question 4, there should be a list of the used and probably measured attributes. Finding the right formalizations can be guided by Table 1 and Figure 2.

At last, the attributes are selected and edited for the actual metric **consumer**. At this step, the mapping of attributes to metrics is carried out. One ontology might have more than one stakeholder and likely require different views. For example, a manager might be more interested in measures giving an overview like annotations to classes ratio. Two knowledge engineers working on different aspects, e.g., the structure and the annotations, need other metrics, e.g., graph-related measures and the count of annotations and classes. Giving the right metrics to the right persons enables them to aid the specific tasks they are working on. More information on this selection process is to be found in section 3.3.

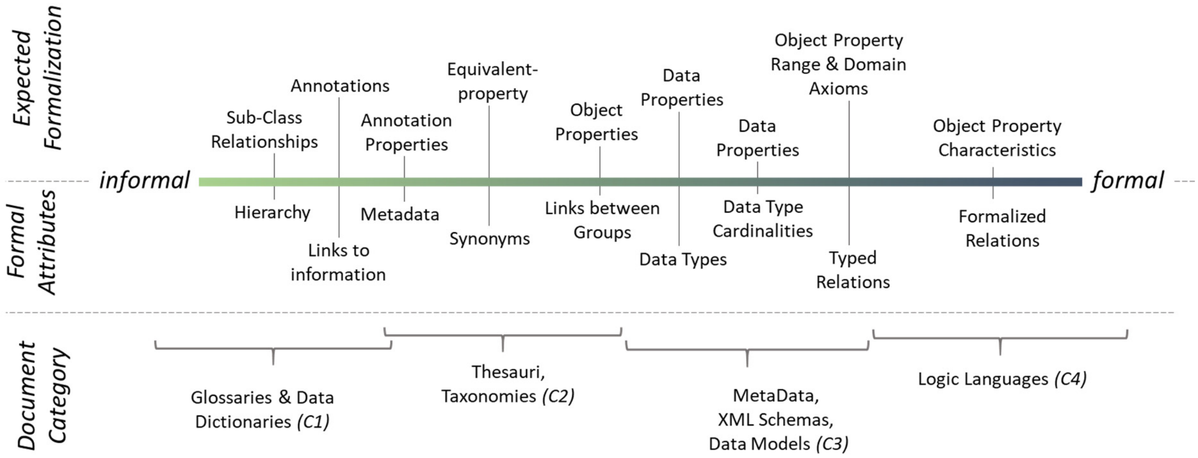

Figure 2: Possible relations between attributes, owl formalizations, and the document categories.

3.2 A Bottom-up Approach for Applying Metrics to Existing Developments

The best-case scenario is an early thorough strategic planning of future ontology developments, including evaluation. More likely, though, is an evaluation scenario for an already existing artifact. However, the strategic questions presented in Table 2 still need to be answered for selecting and using ontology metrics. These questions, though, need to be interpreted in light of the development decisions already undertaken. Figure 3 depicts a proposal for a decision funnel of a bottom-up metric selection process.

At first, an initial look at a large body of metric data shows the axioms used in the ontology. The goal is to identify the implemented structural attributes in the ontology and those that need not be further considered. Thus, it answers the **How**.

Afterward, the next phase considers the existing and planned technical integrations. It answers which of the given measures are necessary for the corresponding **application** and derives possible functional requirements – e.g., every class needs a relation or the necessity for object property characteristics.

The usage context now considers the **what**. Understanding the document category and type based on the previous questions and the indicating attributes of Table 1 answers which kind of ontology has been developed based on the empirical observations.

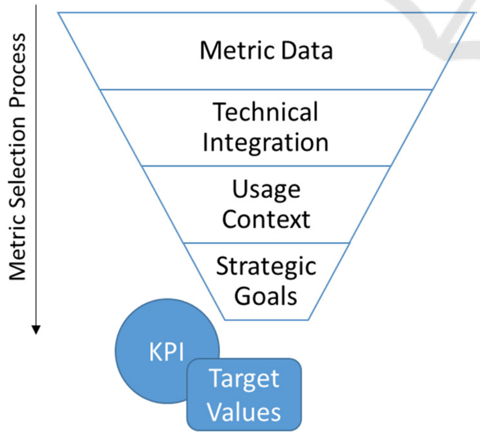

Figure 3: Proposal for a bottom-up metric selection process.

The last step reflects the **strategic** objectives of the ontology. While the driving questions are the same as for the previously described top-down process, the ontology requirements can now be matched with the already modeled reality. In the best case, the modeled ontology already fulfills all the requirements. However, the strategic evaluation can also reveal the necessity to restructure the given artifact, e.g., add more information or delete obsolete elements.

At last, the actual metric selection should take place. Depending on the outcome of the strategic evaluation, metrics should be selected that best capture the progress of future development or, if applicable, the restructurings. Likely, an ontology has more than one set of KPIs, depending on the different **consumers**.

3.3 Selecting and Interpreting the Selected KPIs

Having answered the core-questions, actual metrics need to be selected. Many frameworks propose various measures, and a missing accepted vocabulary for measures leads to heterogeneous definitions: Sometimes, the frameworks propose different names for the same measured elements. The metric ontology by (Reiz & Sandkuhl, 2022c) describes the various frameworks in a joint and formalized terminology. This ontology and the frontend implementation *Metric Explorer* in NEOntometrics (Reiz & Sandkuhl, 2022b) can guide the identification of relevant measures.

While the metric selection is a mandatory step for using ontology metrics, these measures still need to be interpreted. Some of the answered core questions can be translated to value boundaries. For example, if every class needs to have an annotation, the *annotations* to *classes* ratio should be above 1. The historical development of the given measures indicates whether the ontology evolves in favor of the set goals.

Some of the measures might not be translatable to fixed, desired values. Here, the historical data gives information, for example, whether the ontology gets more extensive, interconnected, or thoroughly annotated. It allows an assessment of whether the development efforts are aligned with the set goals.

Further interesting for knowledge engineers is aligning expectations and reality for a made change. At times, a new ontology version has unintended side effects. Examples are unrecognized restructurings by moving or deleting classes. The numeric difference between versions can reveal hidden consequences or unintended alterations.

In this light, observing values that must not be changed is also helpful. Taking the document types of Figure 2 and Table 1, an ontology developed as a document type *data dictionary* should not have complex, formally described object properties. If these values suddenly occur, it can indicate a drift of ontology development and strategy.

4 CONCLUSIONS

Ontology languages like OWL and RDFS give knowledge engineers enormous freedom to model almost any document type or domain. This freedom, however, makes it difficult to assess the quality of an ontology. When developing an explicit specification of a conceptualization, there is more than one way to skin a cat, and the ontology has to be understood with the environment it needs to fit into and its strategic goals.

While ontology metrics offer an objective and reproducible assessment, selecting the right metrics for the given use case is cumbersome and non-trivial. In this position paper, we argue for a metric selection process. The requirements for an ontology can be identified and mapped to ontology metrics using core questions to evaluate an ontology's technical, usage, and strategic setting. This process can be triggered top-down, prior to an ontology development process, or bottom-up for existing ontologies.

While proposals for ontology metrics are not a recent idea, there was an implementation gap for a long time, which was solved with the introduction of OntoMetrics and NEOntometrics. The question of how to put the metrics into use, however, remained. We believe that the proposed metric selection framework can ease the productive use of ontology metrics for quality control and help knowledge engineers use metrics to measure individual progress toward self-set requirements and goals.

The next step for this research endeavor is applying the depicted selection process in real-world ontology development processes. We plan to do a case study with an enterprise that uses ontology metrics to help them select the right ontology metrics for their staff.

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