

Ontology Generation through the Fusion of Partial Reuse and Relation Extraction

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Abstract

Ontology generation—a process to automatically create ontologies from existing knowledge sources—has become a key issue with the emergence of the semantic web. Though many researchers are trying to automate this process by exploiting machine learning and data mining techniques, the results remain under exploration. At the same time, when more and more ontologies are available online, it is important to reuse existing ontologies to a certain extent. In this paper, we present a semi-automatic ontology generation system (OntoGenerator) by partially reusing existing ontologies via a modularization technique and a ranking strategy. In order to enrich the semantics of the generated ontology, we integrate natural language-based, non-taxonomic relation extraction into the system. OntoGenerator is aimed at supporting ontology reuse in semantic indexing. Another objective is to evaluate the maturity of the semantic web by applying its technologies in ontology generation.

Introduction

With the rapid development of the WWW, the amount of online information has increased exponentially. Several approaches using machine learning and data mining techniques have attempted to extract ontologies from existing knowledge bases (Sleeman and Schorlemmer 2003), legacy databases (Maedche and Staab 2001), and text corpora (Brewster and Wilks 2003). One difficulty with those approaches is that background knowledge structure is not always explicitly expressed in the knowledge sources, particularly in the later approaches. At the same time, when more and more ontology library systems (e.g., Protégé, Ontolingua, DAML) and more powerful ontology search engines (e.g., Swoogle, Watson, and OntoSearch) become available, it is reasonable to reuse existing ontologies to a certain extent, so that the process of ontology generation from existing knowledge sources can be accomplished with satisfactory automation and less cost.

We summarize a number of reuse advantages. First, it reduces the human labor involved in developing ontologies

from scratch. Second, it increases the quality of new ontologies because the reused modules have already been verified to a certain degree. Third, when two ontologies share common modules, the mapping process between them becomes simpler because of the reduced heterogeneity. Fourth, ontology reuse can support ontology maintenance. Finally, semantic web users can practice ontology construction through reuse techniques.

In the early stages of ontology development, most ontology designers are reluctant to reuse existing ontologies. The main reason for this include the limited reuse mechanism and supporting tools. For instance, `owl:Imports`—bringing all axioms of the imported ontology into the target ontology—is the only construct that OWL¹ supports for reuse. When a new ontology fully imports a number of ontologies with unneeded portions, its size and complexity become critical issues. Thus, some researchers have instead given their attention to partial reuse. Garu and his colleagues (Garu and Sattler 2007) presented a mechanism of automatic partitioning—dividing an ontology into a number of logically discriminated partitions—based on the $\mathcal{E}$ -connection language (Grau and Kalyanpur 2005). SWOOP² supports a functionality of such partitions. However, it is limited since it is independent from user requirements. For semantic indexing—an attempt to compose semantic description of web documents with meta-data and markups, user requirement plays an important role to achieve a relevant ontology. Therefore, we propose a technique to extract a modular ontology based on user requirements (a desired set of keywords) as well as minimal size and complexity.

Gruber's definition of ontology is *a formal, explicit specification of a shared conceptualization*. This implies that the semantics given in ontologies should be explicit and machine understandable. With respect to this, we favor on explicitness in applying some well-known measures for ontology module selection and ranking. Then, the system generates a customized ontology by integrating some highly relevant modular ontologies. Moreover, we pursued the intuitive idea of semantic enrichment, which is the extraction of non-taxonomic relations from implicit

¹OWL is W3C standard Ontology Web Language
<http://www.w3.org/TR/2003/PR-owl-ref-20031215/>

²<http://www.mindswap.org/2004/SWOOP/>

Table 1: The basic constructors of $\mathcal{SHOIQ}$

Constructor	DL syntax
intersectionOf	$C_1 \sqcap \dots \sqcap C_n$
unionOf	$C_1 \sqcup \dots \sqcup C_n$
complementOf	$\neg C$
oneOf	$\{a_1\} \sqcup \dots \sqcup \{a_n\}$
allValuesFrom	$\forall P.C$
someValuesFrom	$\exists P.C$
maxCardinality	$\leq nP.C$
minCardinality	$\geq nP.C$

knowledge sources (particularly annotated definitions available in the form of `rdfs:comment`) and addition of these relations into the generated ontology. Since verbs play an essential role in the relations between a subject (`owl:Class`) and object (`owl:Class`) (Kavalec and Svaték 2005; Schutz and Buitelaar 2005), verb centric triples such as $\langle \text{Subject}, \text{Verb}, \text{Object} \rangle$ are the major focus of non-taxonomic relations. The idea is developed by utilizing the generated ontology together with natural language parsing techniques. We call this procedure *ontology-based relation extraction*.

In this paper, a semi-automatic ontology generation system (OntoGenerator) is presented by employing existing semantic web technologies in a series of processes, such as ontology search, modularization, module ranking and selection, module integration, relation extraction, and interactive review of the generated ontology. We also evaluate the OntoGenerator system by examining the quality of generated ontologies in comparison to related works. Semantic indexing is designated as a potential application for OntoGenerator.

Preliminaries

Ontology generation through partial reuse is an integrated process that involves ontology modularization—extracting some relevant ontology modules from existing ontologies—and the reuse of those modules as customized ontologies in integration. The formalisms for modular ontologies studied in this paper underlie OWL DL³ that corresponds to the description logics language $\mathcal{SHOIQ}$ (Baader and Sattler 2007; Baader and Nardi 2003). Thus, we briefly introduce its syntax and semantics.

The syntax of $\mathcal{SHOIQ}$ is given by a signature $\mathbf{S}$ and a set of constructors. Signature $\mathbf{S} = \{\mathbf{C} \cup \mathbf{R} \cup \mathbf{I}\}$ is the (disjoint) union of a set $\mathbf{C}$ of atomic concepts ($C_1, C_2, \dots$) representing sets of elements, a set $\mathbf{R}$ of atomic roles ($P_1, P_2, \dots$) representing binary relations between elements, and a set $\mathbf{I}$ of individuals ($a_1, a_2, \dots$) representing elements. Table 1 and 2 describe $\mathcal{SHOIQ}$ constructors and axioms respectively, where n is a positive integer.

The logical entailment $\models$ is defined using the model theoretic semantics⁴. Given signature $\mathbf{S}$, an interpretation $\mathcal{I}$ is a

³<http://www.w3.org/TR/owl-ref/>

⁴<http://www.w3.org/TR/owl-semantics/direct.html>

Table 2: The basic axioms of $\mathcal{SHOIQ}$

Axiom	DL syntax
subClassOf	$C_1 \sqsubseteq C_2$
equivalentClass	$C_1 \equiv C_2$
disjointWith	$C_1 \sqsubseteq \neg C_2$
sameIndividualAs	$\{a_1\} \equiv \{a_2\}$
differentFrom	$\{a_1\} \sqsubseteq \neg \{a_2\}$
subPropertyOf	$P_1 \sqsubseteq P_2$
equivalentProperty	$P_1 \equiv P_2$
inverseOf	$P_1 \equiv P_2^-$
transitiveProperty	$P^+ \sqsubseteq P$
functionalProperty	$\top \sqsubseteq \leq 1P$
inverseFunctionalProperty	$\top \sqsubseteq \leq 1P^-$

Table 3: Some basic interpretations in $\mathcal{SHOIQ}$

Concepts
$(\neg C)^{\mathcal{I}} = \Delta^{\mathcal{I}} \setminus C^{\mathcal{I}}$ $(C_1 \sqcap C_2)^{\mathcal{I}} = C_1^{\mathcal{I}} \cap C_2^{\mathcal{I}}$ $(C_1 \sqcup C_2)^{\mathcal{I}} = C_1^{\mathcal{I}} \cup C_2^{\mathcal{I}}$ $(\forall P.C)^{\mathcal{I}} = \{a \in \Delta^{\mathcal{I}} \mid P^{\mathcal{I}}(a, \neg C) = \emptyset\}$ $(\exists P.C)^{\mathcal{I}} = \{a \in \Delta^{\mathcal{I}} \mid P^{\mathcal{I}}(a, C) \neq \emptyset\}$ $(\leq nP.C)^{\mathcal{I}} = \{a \in \Delta^{\mathcal{I}} \mid \text{NP}^{\mathcal{I}}(a, C) \leq n\}$ $(\geq nP.C)^{\mathcal{I}} = \{a \in \Delta^{\mathcal{I}} \mid \text{NP}^{\mathcal{I}}(a, C) \geq n\}$
Axioms
$(C_1 \sqsubseteq C_2)^{\mathcal{I}} = C_1^{\mathcal{I}} \subseteq C_2^{\mathcal{I}}$ $(P_1 \sqsubseteq P_2)^{\mathcal{I}} = P_1^{\mathcal{I}} \subseteq P_2^{\mathcal{I}}$ $(P^+)^{\mathcal{I}} = \{\forall a_1, a_2, a_3 \in \Delta^{\mathcal{I}} \mid P^{\mathcal{I}}(a_1, a_2) \cap P^{\mathcal{I}}(a_2, a_3) \rightarrow P^{\mathcal{I}}(a_1, a_3)\}$

pair $\mathcal{I} = (\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}})$. In this pair, $\Delta^{\mathcal{I}}$ is a non-empty set called the domain of the interpretation and $\cdot^{\mathcal{I}}$ is the interpretation function that assigns to every $C \in \mathbf{C}$ a subset $C^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$, to every $P \in \mathbf{R}$ a binary relation $P^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$, and to every $a \in \mathbf{I}$ an element $a^{\mathcal{I}} \in \Delta^{\mathcal{I}}$. Table 3 describes some basic interpretations in $\mathcal{SHOIQ}$ where NP is number restriction of role P . An interpretation $\mathcal{I}$ is a model of an ontology O if $\mathcal{I}$ satisfies all axioms in O .

We extend the notion of formal ontology with partial reuse, following the above syntax and semantics.

Definition 1 (Formal Ontology) A formal ontology denoted by O_j is a set of axioms given on signature $\text{Sig}(O_j)$ —which consists of classes ($\mathbf{C}_j$), roles/properties ($\mathbf{R}_j$), and individuals ($\mathbf{I}_j$)—given in DL language $\mathcal{SHOIQ}$. Index j differentiates one ontology from others.

Definition 2 (Ontology Module) An ontology module $O_{jM_k} \subseteq O_j$ is a set of direct axioms that are extracted from Ontology O_j for signature $M_k \subseteq \text{Sig}(O_j)$ where k is the index of the signature.

Definition 3 (PR Ontology) A partially reused (PR) ontology $O_{r_i} = \langle \{O_{jM_k}\}, O_i \rangle$ is a union of a list of selected ontology modules $\{O_{jM_k}\}$ for a number of signatures $\{M_k\} \subseteq \text{Sig}(O_{r_i})$ and the local ontology O_i that reuses $\{O_{jM_k}\}$. Note that $i \neq j$.

Four Well-known Measures for Ontology Selection and Ranking

In this section, we represent four well-known structural measures that are applied to ontology selection and ranking. We mainly adopt these measures from AKTiveRank (Alani and Brewster 2006).

Class Match Measure

The Class Match Measure (CMM) is a name-based measure that is used to search and select ontologies (Ding and Sachs 2004; Buitelaar and Declerck 2004; Alani and Shad-Bolt 2006).

Definition 4 (Class Match Measure) Let O_j be a candidate ontology and T be a set of interested keywords. The class match measure of ontology O_j , denoted by $CMM(O_j)$, is calculated as:

$$\text{Exact Match} : E(O_j, T) = \sum_{C \in C_j} \sum_{t \in T} I(C, t)$$

$$\text{Partial Match} : P(O_j, T) = \sum_{C \in C_j} \sum_{t \in T} J(C, t)$$

$$I(C, t) = \begin{cases} 1 & \text{if label}(C) = t \\ 0 & \text{otherwise} \end{cases}$$

$$J(C, t) = \begin{cases} 1 & \text{if label}(C) \text{ contains } t \\ 0 & \text{otherwise} \end{cases}$$

$$CMM(O_j, T) = \alpha E(O_j, T) + \beta P(O_j, T)$$

It is obvious that ontologies covering all keywords with exact matches are better than those with partial matches. Thus, $\alpha = 0.6$ and $\beta = 0.4$ are the weight factors set up to favor exact matches over partial matches. Note that we consider both the goodness and weakness of the partial match, such that we obtain more related classes and properties as well as irrelevant ones. For instance, we get **Research Student** for keyword “Research” and **Projector** for keyword “Project”. However, we observe that the ratio of relevance is higher than irrelevance because of the multiple keyword search.

Density Measure

For a class, the degree of explicitness is measured primarily with the number of classes and properties that directly belong to the class. The density measure (DEM) of a class is calculated based on the degree of explicitness which takes into account the number of classes and properties connected to the class.

Definition 5 (Density Measure) For any class $C \in C_j$, let $S = \{S_1, S_2, S_3, S_4, S_5, S_6\}$ be the sub-classes, super-classes, siblings, relations, attributes and constraints, of C . The density measure of ontology O_j , $DEM(O_j)$, is computed as follows:

$$DEM(C) = \sum_{i=1}^6 w_i |S_i|, DEM(O_j) = \frac{1}{n} \sum_{i=1}^n DEM(C)$$

where $n = |E(O_j, T)| + |P(O_j, T)|$ is the number of namely-matched classes via CMM. The weight value of each w can be either equally or conditionally distributed.

Semantic Similarity Measure

Ontologies can be viewed as semantic graphs of concepts and relations. Rada (Rada and Blettner 1989) introduced the shortest path-based similarity measure. Its variations have been used in (Maedche and Staab 2001; Weinstein and Birmingham 1999; Alani and ShadBolt 2006). The Semantic Similarity Measure (SSM) examines the semantic connectivity between classes through the shortest path—the path with minimum number of links (via both taxonomic and non-taxonomic relationships) that connects a pair of concepts.

Definition 6 (Semantic Similarity Measure) For any two classes $C_f, C_g \in C_j$, let $C_f \xrightarrow{p} C_g$ be a path $p \in P$ between classes C_f and C_g . The semantic similarity measure of O_j , $SSM(O_j)$, is calculated as:

$$SSM(C_f, C_g) = \frac{1}{\text{length}(\min(p \in P))} \text{ if } f \neq g$$

$$SSM(C_f, C_g) = 1 \text{ if } f = g$$

$$SSM(O_j) = \frac{1}{n} \sum_{f=1}^{n-1} \sum_{g=f+1}^n SSM(C_f, C_g)$$

Betweenness Measure

JUNE (Ding and Kolari 2005) provides a betweenness measure (BEM) to calculate the number of shortest paths that pass through each node in a graph. If the class with the highest BEM value in an ontology is graphically the most central to that ontology.

Definition 7 (Betweenness Measure) The betweenness measure of ontology O_j , symbolized by $BEM(O_j)$, is computed as follows:

$$BEM(O_j) = \frac{1}{n} \sum_{h=1}^n BEM(C_h)$$

$$BEM(C_h) = \sum_{C_f \neq C_g \neq C_h \in C_j} \frac{\sigma_{C_f, C_g}(C_h)}{\sigma_{C_f, C_g}}$$

where σ_{C_f, C_g} is the shortest path from C_f to C_g and $\sigma_{C_f, C_g}(C_h)$ is the number of shortest paths that passes through C_h .

Analysis of Ontology Modularization Techniques & Criteria

The objective of this section is to provide an overview of existing modularization techniques and discuss their fundamental criteria.

The survey in (Seidenberg and Rector 2006) is broadly focused towards comparing a number of techniques including query-based, network partitioning-based, and traversal-based modularization techniques. Query-based methods obtain ontology modules as answers to ontology queries given in SparQL or OWL-QL. Network partitioning-based methods consider ontologies as graphs and exploit graph partitioning algorithms to take out structurally relevant modules. In this strategy, some modules may have only a single class

whereas others hold the whole ontology. Traversal-based modularization methods extract some ontological components (e.g., classes, properties, and individuals) that all are syntactically linked to the user requirements. In (Sperano 2005), modularization is considered as a process to design a new ontology by obtaining modular ontologies from existing ontologies. This is objectively related to our work. Nevertheless, partitioning approaches are mainly discussed.

In the literature, there is a work by (d'Aquin and Sabou 2007) compares the results of ontology selection returned by partitioning-based tools such as *Swoop* and *Pato*⁵, with the results produced by modularization-based tools such as *KMi*⁶ and *Prompt*⁷. The work concluded that modularization is more appropriate than partitioning for the purpose of knowledge selection regarding the user requirements. Therefore, we learned existing modularization techniques and organized some of their criterias as the command ground for our modularization tool in *OntoGenerator*.

Sabou and colleagues (d'Aquin and Motta 2006a) discuss a number of modularization approaches in the literature. These can be divided into two common approaches. The first approach involves including all super/sub-classes of a candidate class in an extracted module. The second approach involves taking out only direct super/sub-classes. It is obvious that the first approach generates large sized ontology modules with extra knowledge. As the motivation of partial reuse is the avoidance of unnecessary size and complexity, our modularization technique follows to the second approach. However, we are aware of a deficiency caused by the second approach, the extracted module might not be able to derive some implicit knowledge linked to both the included and excluded knowledge in the module.

Sabou and colleagues also introduced the following four criteria as general modularization requirements (d'Aquin and Motta 2006b).

- *Modularization criteria reflects selection criteria*: This states that the goal of modularization is to reduce the selected ontology to the relevant sub-parts (or modules).
- *No assumption on the ontology*: The knowledge selection should not require any assumption regarding the ontology representation language (e.g., RDF, DAML, or OWL).
- *Minimal user interaction*: A knowledge selection system cannot expect the user to know well anything concerning the selected ontology or extraction mechanism.
- *Ensuring that output covers both relevant explicit and implicit knowledge*: This encourages the resulting module to include all types of relevant knowledge.

We briefly discuss those criteria for *OntoGenerator*. In our system, the first criterion is mainly considered to assure that the generated ontology reflects the user requirements. We interpret this criterion in terms of relevancy.

Definition 8 (Relevancy) *Relevancy (RL) is a measure of how much the generated PR ontology reflects the user requirements. RL is simply calculated as the number of classes and properties that all totally matched the user requirements (CPM) divided by the total number of keywords (T).*

$$RL = \frac{|CPM|}{|T|}$$

With respect to the second criterion, *OntoGenerator* has a restriction of ontology language. Only OWL ontologies are counted as reusable ontologies in order to simplify the integration process. For the third criterion, user engagement is necessary for the review process, but not necessarily other processes. According to our modularization approach, there is no guarantee to include both explicit and implicit knowledge. Thus, there is a tradeoff between the last criterion and the option of modularization approaches.

OntoGenerator: A Semi-automatic System for Ontology Generation

By studying the fundamental process and analyzing different approaches from the literature (Bontas and Tolktsdorf 2005; Fernandez and Castells 2006; Alani and ShadBolt 2006; Patel and Park 2003; Tartir and Aleman-Meza 2007) we observed a set of commonalities and assembled them into *OntoGenerator*. This is a semi-automatic system that constructs PR ontologies with the assistance of users and ontology tools, through the four serial process modules outlined in Figure1. We present each process module through the step-by-step results of running *OntoGenerator* for an experiment in academic and related domains for a semantic markup process.

Acquisition

This module focuses on the acquisition of both interested keywords for user requirements and reference ontologies for knowledge sources, to generate a PR ontology. It is composed of three serial steps: (1) keyword extraction, (2) ontology search, and (3) ontology selection.

- Keyword extraction is a process for collecting a set of keywords (T) from desired web pages. Simply, T can be obtained via either user selection or use of a tool like *TermExtractor*⁸. T may include keywords given as both nouns (for classes) and verbs (for relations).
- Ontology search is a process for gathering a set of candidate ontologies, $\{O_k\}$, that are all potentially relevant to T . There are two possible ways to do this. The first way involves using an ontology search engine such as *Swoogle*⁹. The second way involves using ontology repositories available online or offline. Table 4 describes the list of URLs returned by *Swoogle* for $T_1 \subseteq T = \{University, Student, Publication, Conference, Professor, supervise, advise, Research, PhD\}$. Additionally, we use the ontologies from OAEI2007 conference track¹⁰ as candidates for $T_2 \subseteq T = \{Committee,$

⁵<http://swserver.cs.vu.nl/partitioning/>

⁶<http://kmi.open.ac.uk/>

⁷<http://protege.stanford.edu/plugins/prompt/prompt.html>

⁸<http://lcl2.di.uniroma1.it/termextractor/>

⁹<http://swoogle.umbc.edu/>

¹⁰<http://nb.vse.cz/svabo/oaei2007/>

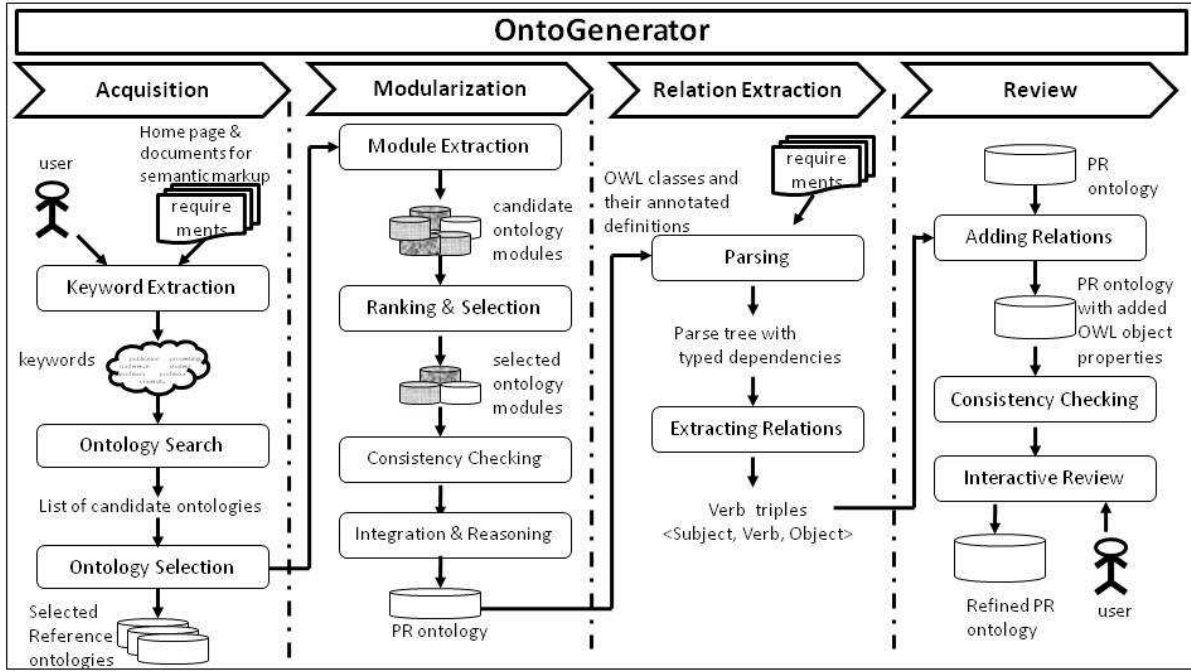


Figure 1: The architecture of OntoGenerator

Table 4: The list of URLs returned by Swoogle for T_1

No.	ontology URL
1	http://protege.stanford.edu/plugins/owl/owl-library/koala.owl
2	http://annotation.semanticweb.org/iswc/iswc.owl
3	http://www.lri.jur.uva.nl/rinke/aargh.owl
4	http://swrc.ontoware.org/swrc-07.owl
5	http://swat.cse.lehigh.edu/onto/univ-bench.owl
6	http://protege.stanford.edu/plugins/owl/owl-library/ka.owl
..	
17	http://www.mondeca.com/owl/mondeca/univ.owl

Member, review, Conference, Workshop, publish }.

- Ontology selection is a process for choosing a set of reference ontologies $\{O_j\}$ for T . We implemented OLap for this selection according to CMM given by Definition 4. OLap sorts $\{O_k\}$ in the order of maximum CMM value, as described in Table 5. A threshold value γ is defined to select $\{O_j\}$, such that any candidate ontology of $\{O_k\}$ whose CMM is greater than γ is chosen as a reference ontology O_j . In this experiment, we simply use $\gamma = 4.0$. It is also possible to define $\gamma = \max(\{CMM(O_k)\})/2$. Note that j and k are the indexes of ontologies.

The result of the acquisition process is a list of reference ontologies, $\{O_j\}$, to reuse for modularization.

Table 5: Reference ontologies resulted by OLap

Ontology for T_1	CMM	Ontology for T_2	CMM
univ.owl	12.0	Conference.owl	9.2
swrc-07.owl	7.6	ekaw.owl	9.0
unib-bench.owl	7.0	edas.owl	8.6
ka.owl	5.6	cmt.owl	6.0
iswc.owl	4.4	sigkdd.owl	5.4
aargh.owl	4.0	iasted.owl	5.0

Modularization

Since the whole of set of reference ontologies may not need to be reused for specific user requirements, our system applies a modularization approach instead of fully reuse. The process of modularization can be further divided into four sub-processes: (1) module extraction, (2) ranking and selection, (3) consistency checking, and (4) integration and reasoning.

- **Module extraction** is the process of extracting modular ontologies from the reference ontologies $\{O_j\}$. In our system, OntoModule is developed in Java as a modularization tool to return a modular ontology O_{jM_k} from each reference ontology O_j . This is done with respect to signature M_k —which is matched with a set of keywords $T_k \subseteq T$. Each O_{jM_k} consists of a set of axioms that represent a number of classes (C)—including only direct super-classes, sub-classes and siblings—together with their properties/roles (P), all direct individuals (a), and restrictions (e.g., `equivalentClass`, `disjointWith`, `inverseOf`, and so on). Suppose

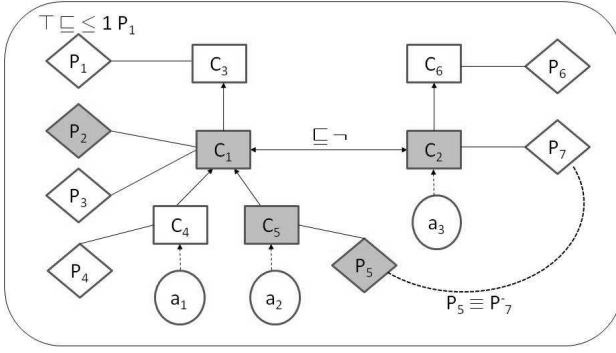


Figure 2: A module extracted for signature $M_k = \{C_1, C_2, C_5, P_2, P_5\}$

$M_k = \{C_1, C_2, C_5, P_2, P_5\}$ is the signature matched with $T_k = \{t_1, t_2, t_3, t_4\}$ such that $\{C_1, C_5\}$ for t_1 , P_2 for t_2 , P_5 for t_3 , and C_5 for t_4 . Then, **OntoModule** will extract O_{jM_k} as shown in Figure 2. Since relevant modules are extracted from each of the reference ontologies $\{O_j\}$, **OntoModule** returns a list of candidate modules, $\{O_{jM_k}\}$, for T .

- **Ranking and selection** is the process of choosing the most relevant modules to create a customized ontology. We developed another Java plugin, **OntoMRank**, for this purpose. Since **OntoModule** considers only direct axioms in its extraction, two shortest-path based measures—SSM and BEM—are not very relevant for **OntoMRank**. According to the experiment result shown in Figure 3, the values of the SSM and BEM are not significant like those of the DEM and CMM. More precisely, the values of SSM and BEM are almost similarly distributed among the modules. Thus, **OntoMRank** focuses only on DEM to choose the most relevant modules from $\{O_{jM_k}\}$. In Table 6, the DEM values ranked among the modules for T_1 are listed together with ontological statistics such as the number of classes (denoted by $|C_j|$) and properties (denoted by $|R_j|$). For the DEM, **OntoMRank** employs two sets of weight distributions with respect to the number of classes and properties matched with input T_M . If the number of classes is bigger than the number of properties, then the weight distribution of the DEM for $S = \{S_1, S_2, S_3, S_4, S_5, S_6\}$ is $w_{1..6} = \{2.0, 2.0, 2.0, 1.5, 1.5, 1.0\}$, otherwise $w_{1..6} = \{1.5, 1.5, 1.5, 2.25, 2.25, 1.0\}$. Using equal weight distribution, it is arguable not to rank the modules accurately. Suppose that there are two modules: one with two classes and three properties and another with three classes and two properties. Assume that neither module has any constraints. In such a case, the DEM values for both modules from the equal distribution are exactly the same. Therefore, we suggest considering a kind of dynamic weight distribution over the input keywords. For each signature M_k , at most one module is selected from $\{O_{jM_k}\}$. The result of **OntoMRank** is shown in Table 6, where `swrc-07-USPCPSAR.owl` has the highest DEM value

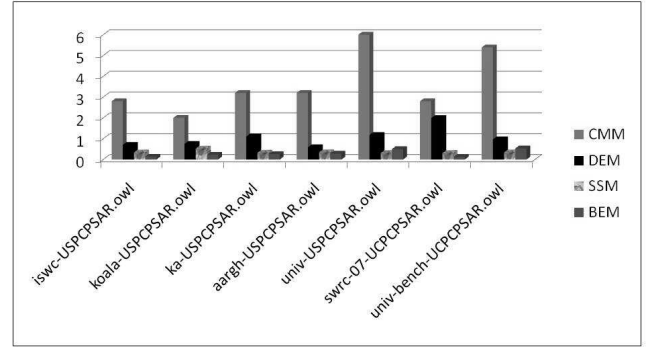


Figure 3: The values of CMM, DEM, SSM and BEM of the modules for T_1

Table 6: The DEM value and ontological statistics among the modules extracted for T_1

Ontology Modules (O_{jM_k})	DEM	$ C_j $	$ R_j $
swrc-07-USPCPSAR.owl	1.99	32	55
univ-USPCPSAR.owl	1.179	33	10
ka-USPCPSAR.owl	1.1	14	51
univ-bench-USPCPSAR.owl	0.963	23	26
koala-USPCPSAR.owl	0.75	9	5
iswc-USPCPSAR.owl	0.7	13	29
aargh-USPCPSAR.owl	0.583	37	20

among the modules for T_1 . Similarly for T_2 , the final module selected from the reference ontologies given in Table 5 is `Conference-CMRCWP.owl`.

- **Consistency checking** is a reasoning process for logically verifying the consistency of each of the extracted modules. It is obvious that each module must be certified for its consistency before integration with other modules. This process is critical for ontology generation through the modularization approach. **Racer**¹¹ is employed for this purpose. We observed from this experiment that **OntoModule** produces modular ontologies in a consistent style without losing any required axiom.
- **Integration & Reasoning** is a process that first creates a PR ontology by integrating selected reusable modules. We use **Protégé OWL API**¹² as an interface model not only to integrate the selected modules but also to generate a PR ontology in OWL. In this experiment, two selected modules for T are integrated as `MyMarkup.owl`¹³ which consists of 60 classes and 85 properties in total. Then, the process includes a reasoning task to ensure the consistency of the integrated ontology by **Racer** and **RacerPorter**. Since the cus-

¹¹<http://www.sts.tu-harburg.de/simr.f.moeller/racer/>

¹²<http://protege.stanford.edu/>

¹³<https://www.comp.nus.edu.sg/~tunnn/MyMarkup.owl>

tomized PR ontology is generated by the integration of the selected ontology modules, the process needs to ensure consistency between the PR ontology and its reused modules. For any two axioms α and β such that $O_{jM_1} \in \{O_{jM_k}\} \models \alpha$ and $O_{jM_2} \in \{O_{jM_k}\} \models \beta$, any query of $\{\alpha, \beta, \alpha \vee \beta, \alpha \wedge \beta\}$ must satisfy in PR ontology O_{r_i} that reuses $\{O_{jM_k}\}$.

Relation Extraction

Though we favor the DEM for the selection of ontology modules, the generated PR ontology might not always be explicit enough for this when the candidate ontologies are developed in simple taxonomies. One possible way to make ontologies explicit is to extract additional non-taxonomic relationships from other implicit forms. This is also called semantic enrichment. In our system, we consider all annotated definitions given via `rdfs:comment` as implicit knowledge source for this relation extraction. This process is accomplished in two serial steps: (1) parsing and (2) extracting relations. A natural language parser and a relation extractor are mainly utilized for this process.

- **Parsing** is the process of expressing a natural language sentence into the form of grammatical tree in order to classify the words in terms of part of speech (e.g., NP, NN, or VP). A parser is a Natural Language Processing (NLP) system for this. Several kinds of parsers exist. While a phrase structure parse represents the nesting of multi-word constituents, a dependency parse represents the dependency between individual words (Buitelaar 2004; Gamallo 2002). A typed dependency parse additionally labels the dependencies with grammatical relations, such as *subject* or *object* (Marneffe and D. Manning 2006). We use the **Stanford Parser**¹⁴, a statistical NLP parser that works out the grammatical structure of sentences into a *parse tree* with *typed dependencies*. Normally, the input of a parser is a sentence or a paragraph; however we mostly use clauses here. The output of the Stanford parser includes a parse tree and a list of collapsed word pairs in dependency, for each input clause. Figure 4 expresses the input and output of the Stanford Parser for an example annotated definition of class *Student*. (Note that the numbers attached in typed dependencies are automatically designated by the Stanford parser only for word identification.)
- **Extracting relation** is the process for obtaining non-taxonomic relations from the annotated definitions. This process transforms implicit knowledge into a form of explicit knowledge. According to the literature (Kavalec and Svaték 2005; Schutz and Buitelaar 2005), verbs play a critical role for both taxonomic and non-taxonomic relations between subjects and objects. Since **OntoGenerator** supports the generation of the well-defined taxonomy of desired classes, extracting additional taxonomic relations is out of our scope. Our intuitive idea is to extract non-taxonomic relations from the available annotated definitions by embedding the generated

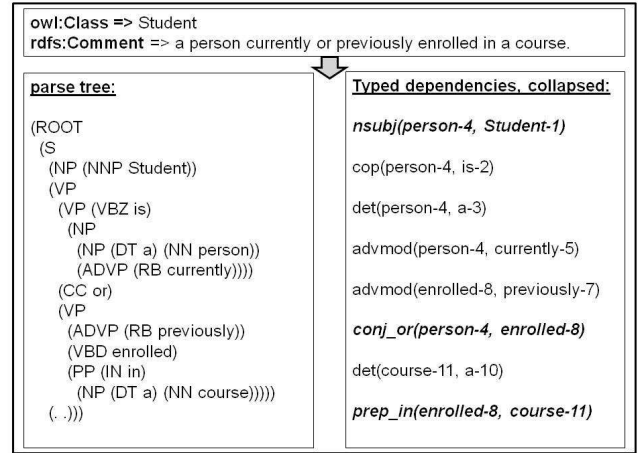


Figure 4: The input and output through Stanford Parser

Table 7: Verb triples extracted by R-Extractor

No.	Verb Triples
1	< chair, leads, event >
2	< postdoc, assigned, research >
3	< professor, gives, lectures >
4	< professor, does, research >
5	< professor, supervises, graduate students >
..	
39	< university, offers, courses >
40	< university, grants, degrees >
41	< research group, works, project >

PR ontology in NLP techniques. This distinguishes our work from that of others. **R-Extractor** is a Java program that we implemented to extract verb triples < Subject, Verb, Object > from the output of the **Stanford Parser**. **R-Extractor**'s purpose is accomplished by the following three steps.

- Capturing a correct subject from the nouns (and noun phrases), which is mostly comparable to one of the OWL classes already defined in the PR ontology.
- Capturing verbs and their related objects by employing a set of pattern rules over a set of five critical typed dependencies (i.e., {*nsubj*, *dobj*, *rcmod*, *conj*, *prep*}) from the grammatical relation hierarchy given in (Marneffe and D. Manning 2006).
- Generating verb triples < Subject, Verb, Object >.

By the example described in Figure 4, “enrolled” is a relation between *person* and *course*. From the known taxonomic (is-a) relationship between *person* and *student* (i.e., “student is a person”) the output of **R-Extractor** is *<student, enrolled, course>*. The result of **R-Extractor** is a list of verb triples as partly described in Table 7. It is obvious that extracting the most relevant verbs through a given ontology may reduce the process of named entity recognition, and thus it is less

¹⁴<http://nlp.stanford.edu/software/lex-parser.html>

complicated while still producing an acceptable result. We conducted an evaluation of R-Extractor in terms of *precision* and *recall* by comparing the set of verb triples extracted by R-Extractor (C_r) with the set of expert-defined triples (C_e). C_{re} is calculated for the correctness of C_r in C_e such that $C_{re} = C_r \cap C_e$.

- Precision $P = \frac{|C_{re}|}{|C_r|}$ is the percentage of correctness by R-Extractor.
- Recall $R = \frac{|C_{re}|}{|C_e|}$ is the percentage of the correctness of R-Extractor, comparing with C_e .

In the experiment, there are 52 classes with annotated definitions given via `rdfs:comment`. The number of extracted triples C_r is 41 whereas C_e is 60 since more than one triple can be extracted from a single sentence. For example, “A professor is a faculty member who not only gives lectures but also does research by supervising graduate students.”. In this experiment, the precision and recall of R-Extractor are 92.69% and 63.33% respectively. We note that the limited number of dependency patterns used in R-Extractor might result a low recall value.

Among the existing ontology learning systems, the work of ReLExt (Schutz and Buitelaar 2005)¹⁵ is similar to our approach. However, ReLExt explores relation triples from a corpus given in the German language utilizing the SCHUG system (Declerck 2001). Even though the tools and support for reuse and learning are increasing, difficulties still exist. The most challenging point from this experiment is relation evaluation. More precisely, there may be overlap in name or semantics both among the extracted verb triples and between those and the existing OWL object properties.

Review

In this process module, we utilize three sub-processes: (1) adding relations, (2) consistency checking and (3) interactive review of the whole PR ontology generated.

- **Adding relation** is a process that transforms the extracted verb triples into OWL object properties as specified in the following.

```
<owl:ObjectProperty df:ID="enrolled">
  <rdfs:domain rdf:resource="#Student"/>
  <rdfs:range rdf:resource="#Course"/>
</owl:ObjectProperty>
```

We employ OLap to resolve name overlapping among the existing and new relations. Alternatively, it can deal with this using WordNet¹⁶.

- **Consistency checking** is done by Racer again for the relation-added PR ontology. Additional checking can also be performed based on a combined reasoning approach (Dong et al. 2004).

¹⁵ReLExt is developed for SmartWeb project in football domain, particularly for FIFA World Cup in Germany, 2006.

¹⁶<http://wordnet.princeton.edu/>

- **Interactive review** is a process that evaluates the generated PR ontology with its added relations in an interactive style. User involvement in this review process is necessary for two reasons: (1) the existence of semantic overlap among the names of relations and (2) the need to systematically structure the indirectly extracted classes (i.e., those that are not directly but necessarily extracted together with the non-taxonomic relations) into the taxonomy instead of easily assigning them as the sub-classes of `owl:Thing`. We realize that current techniques are not adequate to resolve these problems automatically. Even though a PR ontology is carefully generated through many well-developed tools and checked with Racer, it is better for users to check it by practicing semantic indexing or using it in their target information systems. During this review process, the relevancy evaluation is considered to fulfill the aim of OntoGenerator. It assists users in developing a customized OWL ontology through partial reuse. By Definition 8, the relevancy of the generated ontology is calculated. In the given case study, the computed RL value of `MyMarkup.owl` is 0.94. This value proves the feasibility of OntoGenerator.

Related Work

Our idea of OntoGenerator is differentiated from other ontology generation systems (Stuckenschmidt and Klein 2003; Alani and ShadBolt 2006; Maedche and Staab 2001) by a modularization technique and a ranking strategy that rely on explicitness. Since OntoGenerator shares two measures—the CMM and DEM—with AKTiveRank (Alani and ShadBolt 2006), we mainly compare AKTiveRank and OntoMRank—the ranking tool of OntoGenerator. AKTiveRank selects a relevant (full) ontology O_k based on a total score aggregated from the CMM, DEM, SSM and BEM by taking equal weights among the measures. In addition to the equal weight distribution difference between AKTiveRank and OntoMRank, another difference regarding the method of computing the DEM exists. AKTiveRank computes the DEM on $S = \{S_1, S_2, S_3, S_4\}$ denoted for the number of sub-classes, super-classes, siblings, and relations whereas OntoMRank calculates the DEM using additional two measures (attributes and constraints) as given in Definition 5.

Definition 9 (Total AKTiveRank Score) Let $\{O_k\}$ be the set of candidate ontologies to rank for ontology selection, w_i be a weight factor and $M = \{M[1], M[2], M[3], M[4]\} = \{CMM, DEM, SSM, BEM\}$ be four ranking measures.

$$Score(O_k \in \{O_k\}) = \sum_{i=1}^4 w_i \frac{M[i]}{\max_{1 \leq j \leq |\{O_k\}|} M[j]}$$

Values for each measure are normalized to be in the range (0-1) by dividing them by the maximum measure value of all candidate ontologies. The line graph shown in Figure 5 expresses the result of AKTiveRank returned for five different weight distributions among four measures. In all types of weight distribution, `Koala.owl` attained the highest total score. In the case of OntoMRank,

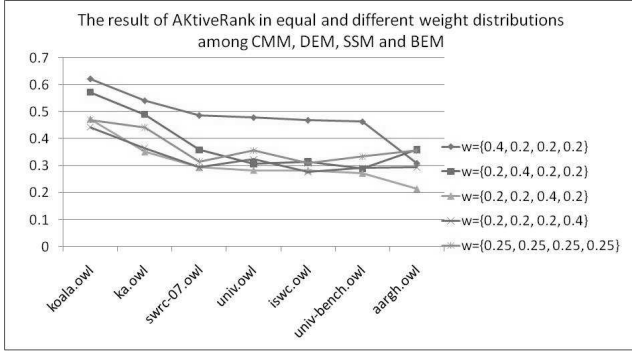


Figure 5: The result of reusable ontologies for T_1 by AKTiveRank

`swrc-07-USPCPSAR.owl` was the most relevant ontology module with the highest DEM value. By Definition 8, the relevancy of `swrc-07-USPCPSAR.owl` is double that of `Koala.owl`.

Because the results of the two ontology ranking tools differ, we evaluate them in terms of quality. For this purpose, we apply the schema measure of *OntoQA* (Tartir and Aleman-Meza 2007). This measure consists of the following three kinds of richness.

- Relationship Richness (RR) measures the explicitness of an ontology's relations. An ontology that contains many relations is richer than a taxonomy with only class-subclass relationships. Formally, the relationship richness (RR) of an ontology is defined as the ratio of the number of relationships (R) to the sum of the number of sub-classes (SC) plus the number of relationships.

$$RR = \frac{|R|}{|SC| + |R|}$$

- Attribute Richness (AR) takes into account the number of attributes of each class that can indicate both the quality of ontology design and the amount of pertinent information. Formally, AR is computed as the number attributes for all classes (att) divided by the number of classes (C).

$$AR = \frac{|att|}{|C|}$$

- Inheritance Richness (IR) measures how well knowledge is grouped into different (sub-)categories in the ontology. Formally, IR is defined as the average number of sub-classes (C_I) per class (C_i), $|H^C(C_I, C_i)|$.

$$IR = \frac{\sum_{C_i \in C} |H^C(C_I, C_i)|}{|C|}$$

It is assumed that an ontology with higher richness values is of better quality. Since we focus on partial reuse and modularization, `koala.owl` as a whole is not comparable to `swrc-07-USPCPSAR.owl` in terms of RR, AR, and IR. Therefore, we extract a module from `koala.owl` titled `Koala-USPCPSAR.owl` that hits for T_1 . Table 8 describes the richness values between the two ontologies resulting from *OntoMRank* and *AKTiveRank*.

Table 8: The quality of ontologies in terms of *OntoQA*'s schema measure

Ontology Modules	RR	AR	IR
<code>swrc-07-USPCPSAR.owl</code>	0.603448	0.625	1.25
<code>koala-USPCPSAR.owl</code>	0.5	0.11	0.66
<code>univ-USPCPSAR.owl</code>	0	0.303	1.15

Note that $\{|R| = 35, |SC| = 23, |C| = 32, |att| = 20, \sum_{C_i \in C} |H^C(C_I, C_i)| = 35\}$ and $\{|R| = 4, |SC| = 4, |C| = 9, |att| = 1, \sum_{C_i \in C} |H^C(C_I, C_i)| = 6\}$ are the statistics of `swrc-07-USPCPSAR.owl` and `koala-USPCPSAR.owl` respectively. Moreover, the CMM value of `swrc-07-USPCPSAR.owl` is 2.8 whereas `koala.owl` and `koala-USPCPSAR.owl` remain 2.0 against T_1 .

In addition, as described in Figure 3 `univ-USPCPSAR.owl` has the highest CMM value. However, its quality in the schema measure is lower than that of `swrc-07-USPCPSAR.owl`. In former experiments with *AKTiveRank* (Alani and ShadBolt 2006), ontology was selected for either single or double keywords. In such cases, the values of the SSM and BEM may be valuable for the selection. According to the result shown in Table 8, we suggest employing only the DEM with respect to explicitness as the quality of ontology generated through *OntoGenerator*.

Conclusion

This paper presented an intuitive approach of semi-automatic ontology generation. *OntoGenerator* is developed using a number of semantic web technologies and Java tools in a series of combined processes including modularization, ranking, and ontology-based relation extraction. The innovative part of *OntoGenerator* involves including all of the processes in a complete pipeline to automate the flow of ontology creation through partial reuse. It is obvious that we can avoid knowledge acquisition problems to a certain extent by relying on existing well-defined ontologies, therefore we can bootstrap the process of ontology building. The Java tools implemented for *OntoGenerator* system, which include *OLap*, *OntoModule*, *OntoMRank*, and *R-Extractor*, are available at <http://www.comp.nus.edu.sg/~tunnn/OntoGenerator/>. According to our experiments, we contend that the prototype of *OntoGenerator* is promising for the process of semantic indexing.

We need to evaluate further the accuracy of *R-Extractor* by improving it with additional dependency patterns as well as by comparing it with other existing systems. *OntoGenerator* will be improved toward a more automatic system. In future experiments, we plan to test *OntoGenerator* in a well-defined and complex domain like medicine or bio-informatics. In addition, we would like to discuss both our experience of integrating ontology modules and the amount of user effort needed in the review process in a more concrete style.

Acknowledgments

This research work is supported by the grants of the projects, ‘Advanced Ontological Rules Language and Tools [R-252-000-249-422]’ and ‘Systematic Design Methods and Tools for Developing Location Aware, Mobile and Pervasive Computing Systems [R-252-000-329-279]’. The authors thank the National University of Singapore for its support of promoting research and development in advanced computing.

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2008

This paper was published in the *Proceedings, Eleventh International Conference on Principles of Knowledge Representation and Reasoning*, edited by Gerhard Brewka and Jérôme Lang (Menlo Park, California: AAAI Press).

The 2008 KR conference was held in Sydney, Australia, 16–19 September, 2008.