Structure-guiding Modular Reasoning for Expressive Ontologies

Changlong Wang[1,3,4], Xiaowang Zhang[1,3], and Zhiyong Feng[2,3,*]

[1] School of Computer Science and Technology, Tianjin University, Tianjin, China
[2] School of Software, Tianjin University, Tianjin, China
[3] Tianjin Key Laboratory of Cognitive Computing and Application, Tianjin, China
[4] School of Computer Science and Engineer Technology, NWNU, Lanzhou, China
* Corresponding author

Abstract. We propose a technique that combine an OWL 2 EL reasoner with an OWL 2 reasoner to classify expressive ontologies. We exploit the information implied by the ontology structure to identify a small non-EL ontology that contains necessary axioms to ensure the completeness. In the process of ontology classification, the bulk of workload is delegated to an efficient OWL 2 EL reasoner and the small part of workload is handled by a less efficient OWL 2 reasoner. Experimental results show that our approach leads to a reasonable task assignment and offers a substantial speedup in ontology classification.

1 Introduction

In practical applications, many commonly used ontologies are covered by the OWL 2 EL to a large degree, e.g., of the 226038 axioms in the version *V14.03e* of NCI ontology, only 67 are outside the OWL 2 EL fragment. The tableau-based OWL 2 reasoners are able to reasoning such ontologies, but they are not efficient due to the high complexity of tableau algorithms for expressive ontologies. The profile-specific OWL 2 EL reasoners are efficient, but they become incomplete if the ontologies contain axioms that are outside the OWL 2 EL fragment. Recently, new approaches have been proposed to improve the reasoning performance for expressive ontologies by combining different reasoners [1, 2]. However, the approach [1] needs to represent an ontology in the decomposed form [3] and the modular reasoner MORe [2] is less efficient because it delegates much work to the inefficient tableau-based OWL 2 reasoner. In this study, we exploit the information implied by the ontology structure [3] to identify a small non-EL subontology that is handled by a less efficient OWL 2 reasoner.

2 Preliminaries

Description Logic Ontology. In this paper, we focus on ontologies expressed in OWL 2 and its profile OWL 2 EL underpinned by description logics (DLs) $\mathcal{SROIQ}$ and $\mathcal{EL}^{++}$, respectively [4]. We refer to individuals, atomic concepts, and atomic roles by calling them *terms*. A set of terms is called a *signature*. We use $\mathcal{O}$ for a DL ontology, $\mathcal{M}$ ($\mathcal{M} \subseteq \mathcal{O}$) for a module, and use $\widetilde{\alpha}$ (resp. $\widetilde{\mathcal{O}}$)for the signature in an axiom α (resp. $\mathcal{O}$)

Ontology Structure Induced by Modules. A module is a subset of an ontology that captures all the knowledge about a specified signature Σ. The $\perp$-module is one basic type of locality-based modules (LBMs) and enjoys the following property that can be used for optimising classification [5]:

Proposition 1. *Let O be a SROIQ ontology, A, B concept names in $\widetilde{O}$, $\Sigma \subseteq \widetilde{O}$ with $A \in \Sigma$, and M a $\perp$-module in O w.r.t. Σ. Then $O \models A \sqsubseteq B$ if and only if $M \models A \sqsubseteq B$.*

A $\perp$-module w.r.t. Σ is denoted by $M^{\perp}_{\widetilde{\Sigma}}$. Different axioms might lead to the same module due to the strong logical interrelation among axioms, such axioms that "cling together" is formalised by the notion of *atom* [3]:

Definition 1. *Given an ontology O, and an axiom set at=$\{\alpha_1, \alpha_2, ..., \alpha_n\} \subseteq O$, if $M^{\perp}_{\widetilde{\alpha_1}}$= $M^{\perp}_{\widetilde{\alpha_2}}$=,...,= $M^{\perp}_{\widetilde{\alpha_n}}$, and for any $\beta \in O \setminus at$,$M^{\perp}_{\widetilde{\beta}} \neq M^{\perp}_{\widetilde{\alpha_i}}$ (i=1,2,...,n). then at is called an $\perp$-atom, denoted by $at^{\perp}$.*

For any module, it either contains all axioms in an atom or none of them. The family of atoms of O is denoted by $AD^{\perp}_{O}$. For each atom $at \in AD^{\perp}_{O}$, the module $M^{\perp}_{\widetilde{at}}$ is denoted by M_{at} and the dependent relation between atoms is induced as follows:

Definition 2. *Let at_1 and at_2 be two atoms in $AD^{\perp}_{O}$, at_1 is dependent on at_2 (written $at_1 \succeq at_2$) if $M_{at_2} \subseteq M_{at_1}$.*

The *atomic decomposition* (AD) of an ontology O is a pair $(AD^{\perp}_{O}, \succeq)$, denoted by $AD^{\perp}_{O,\succeq}$, in which $AD^{\perp}_{O}$ is the set of atoms and $\succeq$ is a partial order over those atoms. The union of all atoms on which a given atom *at* depends is called *principal ideal* of *at* (denoted by $(at]$).

Proposition 2. *[3] Let at be an atom in $AD^{\perp}_{O,\succeq}$, the principal ideal (at] is a module.*

Proposition 3. *[3, Remark 3.10] For each atom at, M_{at} coincides with (at] and M_{at} is the smallest module containing at.*

An atom at_i is called a *top atom* if there exists no a distinct atom at_j such that $at_j \succeq at_i$. Hence an ontology O is the union of several independent modules:

$$O = \bigcup \{(tat] \mid tat \textit{ is a top atom}\} \tag{1}$$

3 Modular Reasoning

AD represents the modular structure of an ontology, the information implied by this structure (especially Proposition 2, Proposition 3, and Equation 1) provide us with two important clues for optimising modular classification: Firstly, for two distinct atoms at_1 and at_2 with $at_1 \succeq at_2$, $(at_2]$ is enough to completely classify all the classed in the module $(at_2]$. Secondly, if not each top atom contains non-EL axioms, it is possible to identify a small non-El module and delegate it to an OWL 2 reasoner for computing the subsumption relation of the following form: (1) $A \sqsubseteq B$ (2) $A \sqcap B \sqsubseteq C$ (3) $A \sqsubseteq$

Algorithm 1 modularClassification

Input: an ontology O
Output: H_O: the classification of O
$M_{\overline{EL}} \leftarrow \emptyset$, $H_{M_{\overline{EL}}} \leftarrow \emptyset$, $H_O \leftarrow \emptyset$
for each $\alpha \in S_{na}$ **do**
  if $\alpha \notin M_{\overline{EL}}$ **then**
    $M_{\overline{EL}} \leftarrow M_{\overline{EL}} \bigcup M_\alpha$ // computing the non-EL subontology
  end if
end for
if $M_{\overline{EL}} = O$ **then**
  $H_O \leftarrow$AR.classify(O)
else
  $H_{M_{\overline{EL}}} \leftarrow$AR.classify($M_{\overline{EL}}$) //classifying the non-EL subontology
  $H_O \leftarrow$ MR.classify($H_{M_{\overline{EL}}} \cup O \setminus M_{\overline{EL}}$)
end if
return H_O

$\exists R.B$ (4) $\exists R.A \sqsubseteq B$ (5) $R \sqsubseteq S$ (6) $A \sqcap \exists R.B \sqsubseteq C$ (7) $\exists R.A \sqcap \exists S.B \sqsubseteq C$ where A, B, and C are atomic concepts or $\top$, and R, S atomic roles. Obviously, these subsumption relations fall into OWL 2 EL. Hence, the computed subsumption relations together with the remaining EL part can be handled by an OWL 2 EL reasoner to obtain complete classification. Let S_{na} be the set of non-EL axioms in an ontology, Algorithm 1 describes the process of classifying OWL 2 ontologies in a modular manner, where AR (Assistant Reasoner) stands for an OWL 2 reasoner and MR (Main Reasoner) for an OWL 2 EL reasoner.

4 Experiment and Evaluation

The proposed approach is implemented in a prototype *SGMR* in which the OWL 2 reasoner and OWL 2 EL reasoner are integrated in a black-box manner. We conduct an experiment on eight commonly used ontologies available from the NCBO BioPortal ontology repository [5]. Table 1 provides statistics of test ontologies and Table 2 shows the experimental results compared with MORe. In Table 2, M_{MORe} (resp. $M_{\overline{EL}}$) represents the non-EL subontology that is delegated to the OWL 2 reasoner in MORe (resp. SGMR), and T_{MORe} (resp. T_{SGMR}) represents the time (in seconds) spent in classifying the whole ontology by MORe (resp. SGMR). In our experiments, ELK 0.4.1 and HermiT 1.3.8[6] are used as OWL 2 EL reasoner and OWL 2 reasoner, respectively. The experimental results show that SGMR delegates a smaller part of workload to the inefficient OWL 2 reasoner and obtain a substantial speedup compared with MORe.

5 Conclusion

In this paper, we present approach to classifying *SROIQ* ontologies by combining an OWL 2 EL with an OWL 2 reasoner. Compared with our previous work [1], we do

[5] http://bioportal.bioontology.org
[6] https://www.cs.ox.ac.uk/isg/tools/

Table 1. Test ontology metrics: number of classes (C), number of roles (R), number of axioms (size), number of non-EL axioms (nonEA), and the DL expressivity (DL)

ontology	C	R	size	nonEA	DL
SYN	14,462	2	15,353	4	*ALF*
CSEO	20,085	91	26,540	14	*ALCH*
Galen	23,141	950	37,696	1,149	*SHIF*
Dermlex	6,106	18	24,452	16	*ALCHF(D)*
Protein	35,470	9	46,698	16	*SH*
NCI	93,413	52	219,224	65	*SH(D)*
UBERON	18,874	189	48,806	1,296	*SRIQ*
EFO	17,892	35	25,173	32	*ALHI*

Table 2. Comparison with MORe on classification time and task assignment.

Ontology	MORe		SGMR	
	M_{MORe}	T_{MORe}	$M_{\overline{EL}}$	T_{SGMR}
SYN	187 (1.2%)	12.6	27 (0.8%)	5.1
CSEO	8,693 (32.8%)	20.3	94 (0.4%)	4.7
Galen	35,976 (95.4%)	25.4	2,165 (5.7%)	3.5
Dermlex	18,347 (75.0%)	17.2	8,219 (33.6%)	3.7
Protein	3,972 (8.5%)	12.6	288 (0.6%)	1.7
NCI	33,760 (15.4%)	104.6	7,151 (3.3%)	17.2
UBERON	14,906 (30.5%)	76.4	12,988 (26.6%)	31.4
EFO	7,348 (29.2%)	64.2	897 (3.6%)	21.3

not need to represent an ontology in the decomposed form. Compared with MORe, our approach delegates a smaller workload to the less efficient OWL 2 reasoner hence offers a substantial speedup in ontology classification.

Acknowledgement. This work is supported by the program of the National Key Research and Development Program of China (2016YFB1000603) and the National Natural Science Foundation of China (NSFC) (61502336, 61373035). Xiaowang Zhang is supported by Tianjin Thousand Young Talents Program.

References

1. C. Wang & Z. Feng. A Novel Combination of Reasoners for Ontology Classification. In: *Proc. of ICTAI-13*, pp.463–468, 2013.
2. A. Armas Romero, B. Cuenca Grau, & I. Horrocks. MORe: Modular Combination of OWL Reasoners for Ontology Classification. In:*Proc. of ISWC-12*, pp. 1–16, 2012.
3. C. Del Vescovo, B. Parsia, U.Sattler, & T. Schneider. The Modular Structure of an Ontology: Atomic decomposition. In: *Proc. of IJCAI-11*, pp.2232-2237, 2011.
4. Pascal Hitzler, Markus Krötzsch, & Sebastian Rudolph. Foundations of Semantic Web Technologies. Chapman and Hall/CRC Press, 2010.
5. B. Cuenca Grau, I. Horrocks, Y. Kazakov, & U. Sattler. Modular Reuse of Ontologies: Theory and Practice. *Journal of Artificial Intelligence Research*, 31(1): 273-318, 2008.
6. Baader, F., Calvanese, D., McGuinness, D., Nardi, D., & Patel-Schneider, P. The Description Logic Handbook: Theory, Implementation, and Applications. Cambridge University Press, 2nd edn. (2007)