

Concurrent Classification of \mathcal{EL} Ontologies

Technical Report

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Abstract. We describe an optimised consequence-based procedure for classification of ontologies expressed in a polynomial fragment $\mathcal{ELH}_{\mathcal{R}^+}$ of the OWL 2 EL profile. A distinguishing property of our procedure is that it can take advantage of multiple processors/cores, which increasingly prevail in computer systems. Our solution is based on a variant of the ‘given clause’ saturation algorithm for first-order theorem proving, where we assign derived axioms to ‘contexts’ within which they can be used and which can be processed independently. We describe an implementation of our procedure within the Java-based reasoner ELK. Our implementation is light-weight in the sense that an overhead of managing concurrent computations is minimal. This is achieved by employing lock-free data structures and operations such as ‘compare-and-swap’. We report on preliminary experimental results demonstrating a substantial speedup of ontology classification on multi-core systems. In particular, one of the largest and widely-used medical ontologies SNOMED CT can be classified in as little as 5 seconds.

1 Introduction

Ontology classification is one of the key reasoning services used in the development of OWL ontologies. The goal of classification is to compute the hierarchical representation of the subclass (a.k.a. ‘is-a’) relations between the classes in the ontology based on their semantic definitions. Ontology classification, and ontology reasoning in general, is a computationally intensive task that can take several minutes and, in extreme cases, even hours to complete. This introduces a considerable delay into the ontology development cycle.

Many works have focused on the development of techniques to reduce classification times. Numerous approaches have been proposed for optimizing the underlying (mostly tableaux-based) procedures by reducing the number of redundant inferences and making the computation more goal-directed. Another way of reducing the classification time, which is studied in this paper, is to perform several inferences at the same time, i.e., concurrently. Concurrent algorithms and data structures have gained substantial practical importance due to the widespread availability of multi-core and multi-processor systems.

Nonetheless, concurrent classification of ontologies is challenging and only few works cover this subject. Approaches range from generic ‘divide-and-conquer’ strategies when the ontology is divided into several independent components

[16] to more specific strategies involving parallel construction of taxonomies [1], concurrent execution of tableau rules [10,11], distributed resolution procedures [14], and MapReduce-based distribution approaches [13]. It remains yet to be seen, however, to what extent these strategies improve classification times for existing ontologies, as evaluation, if provided at all, is often limited and rather inconclusive. As of today, none of the commonly used ontology reasoners, including CEL, FaCT++, HermiT, Pellet, jCEL, or RACER, can make use of multiple processors or cores.

In this paper, we consider a ‘consequence-based’ classification procedure, which works by producing logical consequences from the axioms in the ontology. Such procedures were first introduced for the \mathcal{EL} family of tractable description logics (DLs) [2], which became the basis of the OWL 2 EL profile [12]. Later the \mathcal{EL} -style classification procedures have been formulated for more expressive languages, such as Horn- \mathcal{SHIQ} [7] and \mathcal{ALC} [15]. Consequence-based procedures have several distinguished properties, such as optimal worst-case complexity, ‘pay-as-you-go’ behaviour, and lack of non-determinism (even for expressive DLs like \mathcal{ALC}). In this paper we will demonstrate that such procedures are also particularly suitable for concurrent classification of ontologies.

The contributions of this paper can be summarised as follows:

- (i) We formulate a consequence-based procedure for the fragment $\mathcal{ELH}_{\mathcal{R}^+}$ of an OWL 2 EL profile. The procedure does not require the usual axiom normalisation preprocessing [2] but works directly with the input ontology.
- (ii) We describe a concurrent strategy for saturation of the input axioms under inference rules. The strategy works by assigning axioms to ‘contexts’ in which the inferences can be performed independently, and can be used with arbitrary (deterministic) inference systems.
- (iii) We describe an implementation of our concurrent saturation strategy for $\mathcal{ELH}_{\mathcal{R}^+}$ within a Java-based reasoner ELK. We demonstrate empirically that the concurrent implementation can offer a significant speedup in ontology classification compared to existing highly-optimised reasoners, while not exhibiting a significant overhead for managing concurrent computation as compared to perfectly parallelizable scenarios.

2 Preliminaries

The vocabulary of $\mathcal{ELH}_{\mathcal{R}^+}$ consists of countably infinite sets N_R of (*atomic*) *roles* and N_C of *atomic concepts*. Complex *concepts* and *axioms* are defined recursively using the constructors in Table 1. We use the letters R, S, T for roles, C, D, E for concepts and A, B for atomic concepts. A *concept equivalence* $C \equiv D$ stands for the two inclusions $C \sqsubseteq D$ and $D \sqsubseteq C$. An *ontology* is a finite set of axioms. Given an ontology \mathcal{O} , we write $\sqsubseteq_{\mathcal{O}}^*$ for the smallest reflexive transitive binary relation over roles such that $R \sqsubseteq_{\mathcal{O}}^* S$ holds for all $R \sqsubseteq S \in \mathcal{O}$.

$\mathcal{ELH}_{\mathcal{R}^+}$ has Tarski-style semantics. An *interpretation* \mathcal{I} consists of a non-empty set $\Delta^{\mathcal{I}}$ called the domain of \mathcal{I} and an interpretation function $\cdot^{\mathcal{I}}$ that

Table 1. Syntax and semantics of $\mathcal{ELH}_{\mathcal{R}^+}$

	Syntax	Semantics
<i>Roles:</i>		
atomic role	R	$R^{\mathcal{I}}$
<i>Concepts:</i>		
atomic concept	A	$A^{\mathcal{I}}$
top	\top	$\Delta^{\mathcal{I}}$
conjunction	$C \sqcap D$	$C^{\mathcal{I}} \cap D^{\mathcal{I}}$
existential restriction	$\exists R.C$	$\{x \mid \exists y : \langle x, y \rangle \in R^{\mathcal{I}} \wedge y \in C^{\mathcal{I}}\}$
<i>Axioms:</i>		
concept inclusion	$C \sqsubseteq D$	$C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$
role inclusion	$R \sqsubseteq S$	$R^{\mathcal{I}} \subseteq S^{\mathcal{I}}$
transitive role	$\text{Trans}(T)$	$T^{\mathcal{I}}$ is transitive

assigns to each R a binary relation $R^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$ and to each A a set $A^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$. The interpretation function is extended to complex concepts as shown in Table 1.

An interpretation \mathcal{I} *satisfies* an axiom α (written $\mathcal{I} \models \alpha$) if the corresponding condition in Table 1 holds. If an interpretation \mathcal{I} satisfies all axioms in an ontology \mathcal{O} , then \mathcal{I} is a *model* of \mathcal{O} (written $\mathcal{I} \models \mathcal{O}$). An axiom α is a *consequence* of an ontology \mathcal{O} (written $\mathcal{O} \models \alpha$) if every model of \mathcal{O} satisfies α . A concept C is *subsumed* by D w.r.t. \mathcal{O} if $\mathcal{O} \models C \sqsubseteq D$. *Classification* is the task of computing all subsumptions $A \sqsubseteq B$ between atomic concepts such that $\mathcal{O} \models A \sqsubseteq B$.

3 A Classification Procedure for $\mathcal{ELH}_{\mathcal{R}^+}$

Table 2 lists the inference rules of our classification procedure, which are closely related to the original completion rules for \mathcal{EL}^{++} [2]. The rules operate with two types of axioms: (i) *subsumptions* $C \sqsubseteq D$ and (ii) (*existential*) *implications* $\exists R.C \rightarrow \exists S.D$, where C and D are concepts, and R and S roles. The implications $\exists R.C \rightarrow \exists S.D$ have the same semantic meaning as $\exists R.C \sqsubseteq \exists S.D$; we use the symbol \rightarrow just to distinguish the two types of axioms in the inference rules.

Note that we make a distinction between the premises of a rule (appearing above the horizontal line) and its side conditions (appearing after the colon), and use axioms from \mathcal{O} as the side conditions, not as the premises.

It is easy to see that the inference rules are sound in the sense that every conclusion is always a logical consequence of the premises and the ontology, assuming that the side conditions are satisfied. For all rules except the last one this is rather straightforward. The last rule works similarly to the propagation of universal restrictions along transitive roles if we view axioms $\exists S.C \rightarrow E$ and $\exists T.D \rightarrow E$ as $C \sqsubseteq \forall S^-.E$ and $D \sqsubseteq \forall T^-.E$ respectively. Before we formulate a suitable form of completeness for our system, let us first consider an example.

Example 1. Consider the ontology \mathcal{O} in Figure 1 expressing that a knee joint is a joint that is a part of the knee (1), a leg structure is a structure that is a

Table 2. Inference rules for $\mathcal{ELH}_{\mathcal{R}^+}$

$$\begin{array}{l}
\mathbf{R}_{\sqsubseteq} \frac{C \sqsubseteq D}{C \sqsubseteq E} : D \sqsubseteq E \in \mathcal{O} \\
\mathbf{R}_{\sqcap}^- \frac{C \sqsubseteq D_1 \sqcap D_2}{\begin{array}{l} C \sqsubseteq D_1 \\ C \sqsubseteq D_2 \end{array}} \\
\mathbf{R}_{\exists}^- \frac{C \sqsubseteq \exists R.D}{D \sqsubseteq D} \\
\mathbf{R}_{\top}^+ \frac{C \sqsubseteq C}{C \sqsubseteq \top} : \top \text{ occurs in } \mathcal{O} \\
\mathbf{R}_{\sqcap}^+ \frac{C \sqsubseteq D_1 \quad C \sqsubseteq D_2}{C \sqsubseteq D_1 \sqcap D_2} : D_1 \sqcap D_2 \text{ occurs in } \mathcal{O} \\
\mathbf{R}_{\exists}^+ \frac{C \sqsubseteq D}{\exists S.C \rightarrow \exists S.D} : \exists S.D \text{ occurs in } \mathcal{O} \\
\mathbf{R}_{\mathcal{R}} \frac{D \sqsubseteq \exists R.C \quad \exists S.C \rightarrow E}{D \sqsubseteq E} : R \sqsubseteq_{\mathcal{O}}^* S \\
\mathbf{R}_{\mathcal{T}} \frac{D \sqsubseteq \exists R.C \quad \exists S.C \rightarrow E}{\exists T.D \rightarrow E} : \begin{array}{l} R \sqsubseteq_{\mathcal{O}}^* T \sqsubseteq_{\mathcal{O}}^* S \\ \text{Trans}(T) \in \mathcal{O} \end{array}
\end{array}$$

part of the leg (2), a joint is a structure (3), a knee has location in the leg (4), has-location is more specific than part-of (5), and part-of is transitive (6).

Below we demonstrate how the inference rules in Table 2 can be used to prove that a knee joint is a leg structure. We start with a tautological axiom saying that knee joint is a knee joint and then repeatedly apply the inference rules:

$$\text{KneeJoint} \sqsubseteq \text{KneeJoint} \quad \text{input axiom,} \quad (7)$$

$$\text{KneeJoint} \sqsubseteq \text{Joint} \sqcap \exists \text{isPartOf.Knee} \quad \text{by } \mathbf{R}_{\sqsubseteq} (7), (1), \quad (8)$$

$$\text{KneeJoint} \sqsubseteq \text{Joint} \quad \text{by } \mathbf{R}_{\sqcap}^- (8), \quad (9)$$

$$\text{KneeJoint} \sqsubseteq \exists \text{isPartOf.Knee} \quad \text{by } \mathbf{R}_{\sqcap}^- (8). \quad (10)$$

In the last axiom, we have obtained an existential restriction on knee, which now allows us to start deriving subsumption relations for this concept thanks to \mathbf{R}_{\exists}^- :

$$\text{Knee} \sqsubseteq \text{Knee} \quad \text{by } \mathbf{R}_{\exists}^- (10), \quad (11)$$

$$\text{Knee} \sqsubseteq \exists \text{hasLocation.Leg} \quad \text{by } \mathbf{R}_{\sqsubseteq} (11), (4). \quad (12)$$

Similarly, the last axiom lets us start deriving subsumptions for leg:

$$\text{Leg} \sqsubseteq \text{Leg} \quad \text{by } \mathbf{R}_{\exists}^- (12). \quad (13)$$

$$\begin{aligned}
\text{KneeJoint} &\equiv \text{Joint} \sqcap \exists \text{isPartOf.Knee} & (1) \\
\text{LegStructure} &\equiv \text{Structure} \sqcap \exists \text{isPartOf.Leg} & (2) \\
\text{Joint} &\sqsubseteq \text{Structure} & (3) \\
\text{Knee} &\sqsubseteq \exists \text{hasLocation.Leg} & (4) \\
\text{hasLocation} &\sqsubseteq \text{isPartOf} & (5) \\
\text{Trans(isPartOf)} & & (6)
\end{aligned}$$

Fig. 1. A simple medical ontology describing some anatomical relations

This time, we can use (13) to derive existential implications using the fact that $\exists \text{hasLocation.Leg}$ and $\exists \text{isPartOf.Leg}$ occur in \mathcal{O} :

$$\exists \text{hasLocation.Leg} \rightarrow \exists \text{hasLocation.Leg} \quad \text{by } \mathbf{R}_{\exists}^{\dagger} \text{ (13)}, \quad (14)$$

$$\exists \text{isPartOf.Leg} \rightarrow \exists \text{isPartOf.Leg} \quad \text{by } \mathbf{R}_{\exists}^{\dagger} \text{ (13)}. \quad (15)$$

The last implication, in particular, can be used to replace the existential restriction in (12) using $\text{hasLocation} \sqsubseteq_{\mathcal{O}}^* \text{isPartOf}$, which is a consequence of (5):

$$\text{Knee} \sqsubseteq \exists \text{isPartOf.Leg} \quad \text{by } \mathbf{R}_{\mathcal{H}} \text{ (12), (15)}. \quad (16)$$

Similarly, we can derive a new implication using $\text{hasLocation} \sqsubseteq_{\mathcal{O}}^* \text{isPartOf} \sqsubseteq_{\mathcal{O}}^* \text{isPartOf}$ and transitivity of isPartOf (6):

$$\exists \text{isPartOf.Knee} \rightarrow \exists \text{isPartOf.Leg} \quad \text{by } \mathbf{R}_{\mathcal{T}} \text{ (12), (15)}. \quad (17)$$

This implication can now be used to replace the existential restriction in (10):

$$\text{KneeJoint} \sqsubseteq \exists \text{isPartOf.Leg} \quad \text{by } \mathbf{R}_{\mathcal{H}} \text{ (10), (17)}. \quad (18)$$

Finally, we “construct” the definition of leg structure (2) using (3) and the fact that the concept $\text{Structure} \sqcap \exists \text{isPartOf.Leg}$ occurs in \mathcal{O} :

$$\text{KneeJoint} \sqsubseteq \text{Structure} \quad \text{by } \mathbf{R}_{\sqsubseteq} \text{ (9), (3)}, \quad (19)$$

$$\text{KneeJoint} \sqsubseteq \text{Structure} \sqcap \exists \text{isPartOf.Leg} \quad \text{by } \mathbf{R}_{\sqcap}^{\dagger} \text{ (18), (19)}, \quad (20)$$

$$\text{KneeJoint} \sqsubseteq \text{LegStructure} \quad \text{by } \mathbf{R}_{\sqsubseteq} \text{ (20), (2)}. \quad (21)$$

We have thus proved that a knee joint is a leg structure.

In the above example we have demonstrated that a consequence subsumption $\text{KneeJoint} \sqsubseteq \text{LegStructure}$ can be derived using the inference rules in Table 2 once we start with a tautology $\text{KneeJoint} \sqsubseteq \text{KneeJoint}$. It turns out that all implied subsumption axioms with KneeJoint on the left-hand-side and a concept occurring in the ontology on the right-hand-side can be derived in this way:

Theorem 1. *Let \mathbf{S} be any set of axioms closed under the inference rules in Table 2. For all concepts C and D such that $C \sqsubseteq C \in \mathbf{S}$ and D occurs in \mathcal{O} we have $\mathcal{O} \models C \sqsubseteq D$ implies $C \sqsubseteq D \in \mathbf{S}$.*

It follows from Theorem 1 that one can classify \mathcal{O} by exhaustively applying the inference rules to the initial set of tautologies $\text{input} = \{A \sqsubseteq A \mid A \text{ is an atomic concept occurring in } \mathcal{O}\}$.

Corollary 1. *Let \mathbf{S} be the closure of input under the inference rules in Table 2. Then for all atomic concepts A and B occurring in \mathcal{O} we have $\mathcal{O} \models A \sqsubseteq B$ if and only if $A \sqsubseteq B \in \mathbf{S}$.*

Finally, we note that if all initial axioms $C \sqsubseteq D$ are such that both C and D occur in \mathcal{O} (as is the case for the set input defined above), then the inference rules derive only axioms of the form (i) $C \sqsubseteq D$ and (ii) $\exists R.C \rightarrow E$ with C, D, E and R occurring in \mathcal{O} . There is only a polynomial number of such axioms, and their saturation under the inference rules can be computed in polynomial time.

Proof. The proof of Theorem 1 is by contrapositive: we will demonstrate that for all $C \sqsubseteq C \in \mathcal{O}$ and D occurring in \mathcal{O} we have $C \sqsubseteq D \notin \mathbf{S}$ implies $\mathcal{O} \not\models C \sqsubseteq D$. This we accomplish by constructing a model \mathcal{I} of \mathcal{O} satisfying $C^{\mathcal{I}} \not\subseteq D^{\mathcal{I}}$ for all such $C \sqsubseteq D \notin \mathbf{S}$. The interpretation \mathcal{I} is defined as follows:

$$\begin{aligned}\Delta^{\mathcal{I}} &= \{x_C \mid C \sqsubseteq C \in \mathbf{S}\}, \\ A^{\mathcal{I}} &= \{x_C \mid C \sqsubseteq A \in \mathbf{S}\}, \\ S^{\mathcal{I}} &= \text{direct}(S) \cup \text{transitive}(S),\end{aligned}$$

where

$$\begin{aligned}\text{direct}(S) &= \{\langle x_C, x_D \rangle \mid \text{there exists } R \text{ s.t. } R \sqsubseteq_{\mathcal{O}}^* S \text{ and } C \sqsubseteq \exists R.D \in \mathbf{S}\}, \\ \text{transitive}(S) &= \{\langle x_{C_0}, x_{C_n} \rangle \mid \text{there exist } T, (R_i)_{i=1}^n \text{ and } (C_i)_{i=1}^{n-1}, n \geq 2 \text{ s.t.} \\ &\quad T \sqsubseteq_{\mathcal{O}}^* S, (R_i \sqsubseteq_{\mathcal{O}}^* T)_{i=1}^n, \text{Trans}(T) \in \mathcal{O} \text{ and } (C_{i-1} \sqsubseteq \exists R_i.C_i \in \mathbf{S})_{i=1}^n\}.\end{aligned}$$

We will now prove the following two properties for all concepts C and D .

$$\text{If } x_C \in \Delta^{\mathcal{I}} \text{ and } C \sqsubseteq D \in \mathbf{S}, \text{ then } x_C \in D^{\mathcal{I}}. \quad (22)$$

$$\text{If } D \text{ occurs in } \mathcal{O} \text{ and } x_C \in D^{\mathcal{I}}, \text{ then } C \sqsubseteq D \in \mathbf{S}. \quad (23)$$

Proof of (22) is by structural induction on D :

- Case $D = A$. If $x_C \in \Delta^{\mathcal{I}}$ and $C \sqsubseteq A \in \mathbf{S}$, then $x_C \in A^{\mathcal{I}}$ by the definition of $A^{\mathcal{I}}$.
- Case $D = \top$. If $x_C \in \Delta^{\mathcal{I}}$, then $x_C \in \top^{\mathcal{I}}$ by the semantics of \top .
- Case $D = D_1 \sqcap D_2$. Suppose $x_C \in D^{\mathcal{I}}$ and $C \sqsubseteq (D_1 \sqcap D_2) \in \mathbf{S}$. Then $C \sqsubseteq D_i \in \mathbf{S}$ for $i = 1, 2$ by rule \mathbf{R}_{\sqcap} . Applying the induction hypothesis (22) to

$x_C \in \Delta^{\mathcal{I}}$ and $C \sqsubseteq D_i \in \mathbf{S}$ we obtain $x_C \in D_i^{\mathcal{I}}$, from which $x_C \in (D_1 \sqcap D_2)^{\mathcal{I}}$ follows by the semantics of \sqcap .

- Case $D = \exists S.D'$. Suppose $x_C \in \Delta^{\mathcal{I}}$ and $C \sqsubseteq (\exists S.D') \in \mathbf{S}$. By rule \mathbf{R}_{\exists}^- we have $D' \sqsubseteq D' \in \mathbf{S}$, so $x_{D'} \in \Delta^{\mathcal{I}}$. Applying the induction hypothesis (22) to $x_{D'} \in \Delta^{\mathcal{I}}$ and $D' \sqsubseteq D' \in \mathbf{S}$ we obtain $x_{D'} \in D'^{\mathcal{I}}$. Also, since $S \sqsubseteq_{\mathcal{O}}^* S$ and $C \sqsubseteq (\exists S.D') \in \mathbf{S}$, we have $\langle x_C, x_{D'} \rangle \in \text{direct}(S) \subseteq S^{\mathcal{I}}$ by the definition $S^{\mathcal{I}}$. Thus $x_C \in (\exists S.D')^{\mathcal{I}}$ follows by the semantics of \exists .

Proof of (23) is by structural induction on D :

- Case $D = A$. If $x_C \in A^{\mathcal{I}}$, then $C \sqsubseteq A \in \mathbf{S}$ by the definition of $A^{\mathcal{I}}$.
- Case $D = \top$. Suppose \top occurs in \mathcal{O} and $x_C \in \top^{\mathcal{I}} = \Delta^{\mathcal{I}}$. Then $C \sqsubseteq C \in \mathbf{S}$ by the definition of $\Delta^{\mathcal{I}}$, from which $C \sqsubseteq \top \in \mathbf{S}$ follows by rule \mathbf{R}_{\top}^+ .
- Case $D = D_1 \sqcap D_2$. Suppose $D_1 \sqcap D_2$ occurs in \mathcal{O} and $x_C \in (D_1 \sqcap D_2)^{\mathcal{I}}$. Then $x_C \in D_i^{\mathcal{I}}$ for $i = 1, 2$ by the semantics of \sqcap and each D_i occurs in \mathcal{O} , so applying the induction hypothesis (23) $x_C \in D_i^{\mathcal{I}}$ we obtain $C \sqsubseteq D_i \in \mathbf{S}$, from which $C \sqsubseteq (D_1 \sqcap D_2) \in \mathbf{S}$ follows by rule \mathbf{R}_{\sqcap}^+ as $D_1 \sqcap D_2$ occurs in \mathcal{O} .
- Case $D = \exists S.D'$. Suppose $\exists S.D'$ occurs in \mathcal{O} and $x_C \in (\exists S.D')^{\mathcal{I}}$. By the semantics of \exists there exists some element $x_{C'} \in \Delta^{\mathcal{I}}$ such that $\langle x_C, x_{C'} \rangle \in S^{\mathcal{I}}$ and $x_{C'} \in D'^{\mathcal{I}}$. $\exists S.D'$ occurs in \mathcal{O} implies D' occurs in \mathcal{O} ; applying the induction hypothesis (23) to $x_{C'} \in D'^{\mathcal{I}}$ we obtain $C' \sqsubseteq D' \in \mathbf{S}$, from which $\exists S.C' \rightarrow \exists S.D' \in \mathbf{S}$ follows by rule \mathbf{R}_{\exists}^+ as $\exists S.D'$ occurs in \mathcal{O} . Thus, since $\exists S.D' = D$, we have $\exists S.C' \rightarrow D \in \mathbf{S}$. Now, since $\langle x_C, x_{C'} \rangle \in S^{\mathcal{I}}$, by the definition of $S^{\mathcal{I}}$ either (i) $\langle x_C, x_{C'} \rangle \in \text{direct}(S)$ or (ii) $\langle x_C, x_{C'} \rangle \in \text{transitive}(S)$.

In case (i) there exists R such that $R \sqsubseteq_{\mathcal{O}}^* S$ and $C \sqsubseteq \exists R.C' \in \mathbf{S}$; the desired $C \sqsubseteq D \in \mathbf{S}$ then follows by rule $\mathbf{R}_{\mathcal{H}}$ applied to $C \sqsubseteq \exists R.C'$ and $\exists S.C' \rightarrow D$.

In case (ii) there exist T , $(R_i)_{i=1}^n$ and $(C_i)_{i=1}^{n-1}$, $n \geq 2$ such that $T \sqsubseteq_{\mathcal{O}}^* S$, $(R_i \sqsubseteq_{\mathcal{O}}^* T)_{i=1}^n$, $\text{Trans}(T) \in \mathcal{O}$ and $(C_{i-1} \sqsubseteq \exists R_i.C_i \in \mathbf{S})_{i=1}^n$, $C_0 = C$, $C_n = C'$. Applying $\mathbf{R}_{\mathcal{T}}$ to $C_{n-1} \sqsubseteq \exists R_n.C'$ and $\exists S.C' \rightarrow D$ we obtain $\exists T.C_{n-1} \rightarrow D \in \mathbf{S}$. Then applying $\mathbf{R}_{\mathcal{T}}$ iteratively for i from $n-1$ down to 1 to $C_{i-1} \sqsubseteq \exists R_i.C_i$ and $\exists T.C_i \rightarrow D$ we at each step obtain $\exists T.C_{i-1} \rightarrow D \in \mathbf{S}$, therefore $\exists T.C_i \rightarrow D \in \mathbf{S}$ for all $0 \leq i < n$, in particular for $i = 1$. Finally, applying $\mathbf{R}_{\mathcal{H}}$ to $C \sqsubseteq \exists R_1.C_1$ and $\exists T.C_1 \rightarrow D$ we obtain the desired $C \sqsubseteq D \in \mathbf{S}$.

Having proved (22) and (23), we can now show that \mathcal{I} is a model of \mathcal{O} . It is easy check that the interpretation of roles in \mathcal{I} satisfies all role inclusion and transitivity axioms in \mathcal{O} . For concept inclusion axioms consider any $D \sqsubseteq E$ in \mathcal{O} and let x_C be an arbitrary element of $\Delta^{\mathcal{I}}$. If $x_C \in D^{\mathcal{I}}$, then $C \sqsubseteq D \in \mathbf{S}$ by (23) as D occurs in \mathcal{O} . Then $C \sqsubseteq E \in \mathbf{S}$ by rule \mathbf{R}_{\sqsubseteq} , so $x_C \in E^{\mathcal{I}}$ by (22). Thus $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$ and \mathcal{I} is a model of \mathcal{O} .

Finally, consider any C and D such that $C \sqsubseteq C \in \mathbf{S}$ and D occurs in \mathcal{O} . We will show that $C \sqsubseteq D \notin \mathbf{S}$ implies $\mathcal{O} \not\models C \sqsubseteq D$. Suppose $C \sqsubseteq D \notin \mathbf{S}$. We have $x_C \in \Delta^{\mathcal{I}}$ by the definition of $\Delta^{\mathcal{I}}$, $x_C \in C^{\mathcal{I}}$ by (22) and $x_C \notin D^{\mathcal{I}}$ by (23). This shows that $C^{\mathcal{I}} \not\subseteq D^{\mathcal{I}}$ and, since \mathcal{I} is a model of \mathcal{O} , proves $\mathcal{O} \not\models C \sqsubseteq D$. This completes the proof of Theorem 1. \square

Algorithm 1: saturate(input): saturation of axioms under inference rules

Data: input: set of input axioms

Result: the saturation of input is computed in processed

```
1 scheduled ← input;
2 processed ← ∅;
3 while scheduled ≠ ∅ do
4   axiom ← scheduled.poll();
5   if not processed.contains(axiom) then
6     processed.add(axiom);
7     for conclusion ∈ deriveConclusions(processed, axiom) do
8       scheduled.put(conclusion);
```

4 Concurrent Saturation under Inference Rules

In this section we describe a general approach of saturating a set of axioms under inference rules. We first describe a high level procedure and then introduce a refined version which facilitates concurrent execution of the inference rules.

4.1 The Basic Saturation Strategy

The basic strategy for computing a saturation of the input axioms under inference rules can be described by Algorithm 1. The algorithm operates with two collections of axioms: the queue of ‘scheduled’ axioms for which the rules have not been yet applied, initialized with the input axioms, and the set of ‘processed’ axioms for which the rules are already applied, initially empty. The queue of scheduled axiom is repeatedly processed in the while loop (lines 3–8): if the next scheduled axiom has not been yet processed (line 5), it is moved to the set of processed axioms (line 6), and every conclusion of inferences involving this axiom and the processed axioms is added to the queue of scheduled axioms. This strategy is closely related to the ‘given clause algorithm’ used in saturation-based theorem proving for first-order logic (see, e.g., [3]).

Soundness, completeness, and termination of Algorithm 1 is a consequence of the following (semi-) invariants that can be proved by induction:

- (i) Every scheduled and processed axiom is either an input axiom, or is obtained by an inference rule from the previously processed axioms (soundness).
- (ii) Every input axiom and every conclusion of inferences between processed axioms occurs either in the processed or scheduled axioms (completeness).
- (iii) In every iteration of the while loop (lines 3–8) either the set of processed axiom increases, or, otherwise, it remains the same, but the queue of scheduled axioms becomes shorter (termination).

Therefore, when the algorithm terminates, the saturation of the input axioms under the inference rules is computed in the set of processed axioms.

The basic saturation strategy described in Algorithm 1 can already be used to compute the saturation concurrently. Indeed, the while loop (lines 3–8) can be executed from several independent workers, which repeatedly take the next axiom from the shared queue of scheduled axiom and perform inferences with the shared set of processed axioms. To remain correct with multiple workers, it is essential that Algorithm 1 adds the axiom to the set of processed axioms in line 6 before deriving conclusions with this axiom, not after that. Otherwise, it may happen that two workers simultaneously process two axioms between which an inference is possible, but will not be able to perform this inference because neither of these axioms is in the processed set.

4.2 The Refined Saturation Strategy

In order to implement Algorithm 1 in a concurrent way, one first has to insure that the shared collections of processed and scheduled axioms can be safely accessed and modified from different workers. In particular, one worker should be able to derive conclusions in line 7 at the same time when another worker is inserting an axiom into the set of processed axioms. The easiest way to address this problem is to guard every access to the shared collection using locks. But this will largely defeat the purpose of concurrent computation, since workers will have to wait for each other in order to proceed.

Below we describe a lock-free solution to this problem. The main idea is to distribute the axioms according to ‘contexts’ in which the axioms can be used as premises of inference rules and which can be processed independently by workers. Formally, let \mathcal{C} be a finite set of *contexts*, and `getContexts(axiom)` a function assigning a non-empty subset of contexts for every axiom such that, whenever an inference between several axioms is possible, the axioms will have at least one common context assigned to them. Furthermore, assume that every context has its own queue of scheduled axiom and a set of processed axioms (both initially empty), which we will denote by `context.scheduled` and `context.processed`.

The refined saturation strategy is described in Algorithm 2. The key idea of the algorithm is based on the notion of active context. We say that a context is *active* if the scheduled queue for this context is not empty. The algorithm maintains the queue of active contexts to preserve this invariant. For every input axiom, the algorithm takes every context assigned to this axiom and adds this axiom to the queue of the scheduled axioms for this context (lines 2–4). Because the queue of scheduled axiom becomes non-empty, the context is *activated* by adding it to the queue of active contexts (line 5).

Afterwards, each active context is repeatedly processed in the loop (lines 6–17) by essentially performing similar operations as in Algorithm 1 but with the context-local collections of scheduled and processed axioms. The only difference is that the conclusions of inferences computed in line 14 are inserted into (possibly several) sets of scheduled axioms for the contexts assigned to this conclusion, in a similar way as it is done for the input axiom. Once the context is processed, i.e., the queue of the scheduled axioms becomes empty and the loop quits at line 8, the context is deactivated (line 18).

Algorithm 2: saturate(input): saturation of axioms under inference rules

Data: input: set of input axioms
Result: the saturation of input is computed in context.processed

```
1 activeContexts ← ∅;
2 for axiom ∈ input do
3   for context ∈ getContexts(axiom) do
4     context.scheduled.add(axiom);
5     activeContexts.activate(context);
6 loop
7   context ← activeContexts.poll();
8   if context = null then break;
9   loop
10    axiom ← context.scheduled.poll();
11    if axiom = null then break;
12    if not context.processed.contains(axiom) then
13      context.processed.add(axiom);
14      for conclusion ∈ deriveConclusions(context.processed, axiom) do
15        for conclusionContext ∈ getContexts(conclusion) do
16          conclusionContext.scheduled.add(conclusion);
17          activeContexts.activate(conclusionContext);
18    activeContexts.deactivate(context);
```

Similar to Algorithm 1, the main loop in Algorithm 2 (lines 6–17) can be processed concurrently by several workers. The advantage of the refined algorithm, however, is that it is possible to perform inferences in line 14 without locking the (context-local) set of processed axioms provided we can guarantee that no context is processed by more than one worker at a time. For this, it is sufficient to ensure that a context is never inserted into the queue of active contexts if it is already there or it is being processed by a worker. It seems that this can be easily achieved using a flag, which is set to true when a context is activated and set to false when a context is deactivated—a context is added to the queue only the first time the flag is set to true:

<u>activeContexts.activate (context):</u> if not context.isActive then context.isActive ← true ; activeContexts.put (context);	<u>activeContexts.deactivate (context):</u> context.isActive ← false ;
--	--

Unfortunately, this strategy does not work correctly with multiple workers: it can well be the case that two workers try to activate the same context at the same time, both see that the flag is false, set it to true, and insert the context into the queue two times. To solve this problem we would need to ensure that when two workers are trying to change the value of the flag from false to true, only one of them succeeds. This can be achieved without locking by using an

atomic operation ‘compare-and-swap’ which tests and updates the value of the flag in one instruction. Algorithm 3 presents a safe way of activating contexts.

Algorithm 3: `activeContexts.activate(context)`

```

1 if context.isActive.compareAndSwap(false, true) then
2   activeContexts.put(context);

```

Deactivation of contexts in the presence of multiple workers is also not as easy as just setting the value of the flag to false. The problem is that during the time after quitting the loop in line 8 and before deactivation of context in line 18, some other worker could insert an axiom into the queue of scheduled axioms for this context. Because the flag was set to true at that time, the context will not be inserted into the queue of active contexts, thus we end up with a context which is active in the sense of having a non-empty scheduled queue, but not activated according to the flag. To solve this problem, we perform an additional emptiness test for the scheduled axioms as shown in Algorithm 4.

Algorithm 4: `activeContexts.deactivate(context)`

```

1 context.isActive ← false;
2 if context.scheduled ≠ ∅ then activeContexts.activate(context);

```

5 Implementation

In this section we describe an implementation of the inference rules for $\mathcal{ELH}_{\mathcal{R}^+}$ in Table 2 using the refined concurrent saturation strategy presented in Section 4.2. There are two functions in Algorithm 2 that we need to explain how to implement, namely `getContexts(axiom)` and `deriveConclusions(processed, axiom)`.

Recall that the function `getContexts(axiom)` is required to assign a set of contexts to every axiom such that, whenever an inference between several axioms is possible, the premises will have at least one context in common. This is necessary in order to ensure that no inference between axioms is lost because the inferences are applied only locally within contexts. A simple solution would be to use the inference rules themselves as contexts and assign to every axiom the set of inference rules where it can participate. Unfortunately, this strategy does not provide a sufficient number of contexts to be suitable for concurrent rule applications. To come up with a better solution, note that all premises of the inference rules in Table 2 always have a common concept denoted as C . Instead of assigning axioms with the rules where they can be used, we can assign them with the set of concepts that match the respective position of C in the rule applications. This idea leads to the implementation described in Algorithm 5.

Algorithm 5: getContexts(axiom)

```
1 result  $\leftarrow \emptyset$ ;  
  // matching the premises of the rules  $\mathbf{R}_{\sqsubseteq}$ ,  $\mathbf{R}_{\sqcap}^-$ ,  $\mathbf{R}_{\sqcup}^-$ ,  $\mathbf{R}_{\sqcap}^+$ ,  $\mathbf{R}_{\sqcup}^+$ ,  $\mathbf{R}_{\sqcup}^+$   
2 if axiom match  $C \sqsubseteq D$  then result.add( $C$ );  
  // matching the left premise of the rules  $\mathbf{R}_{\mathcal{H}}$  and  $\mathbf{R}_{\mathcal{T}}$   
3 if axiom match  $D \sqsubseteq \exists R.C$  then result.add( $C$ );  
  // matching the right premise of the rules  $\mathbf{R}_{\mathcal{H}}$  and  $\mathbf{R}_{\mathcal{T}}$   
4 if axiom match  $\exists S.C \rightarrow E$  then result.add( $C$ );  
5 return result;
```

To implement the other function `deriveConclusions(processed, axiom)`, we need to compute the conclusions of all inference rules in which one premise is axiom and remaining premises come from `processed`. A naïve implementation would iterate over all possible subsets of such premises, and try to match them to the inference rules. To avoid unnecessary enumerations, we use index data structures to quickly find applicable inference rules. For example, for checking the side conditions of the rule \mathbf{R}_{\sqcap}^+ , for every concept D occurring in the ontology \mathcal{O} we store a set of concepts with which D co-occur in conjunctions:

$$D.\text{rightConjuncts} = \{D' \mid D \sqcap D' \text{ occurs in } \mathcal{O}\},$$
$$D.\text{leftConjuncts} = \{D' \mid D' \sqcap D \text{ occurs in } \mathcal{O}\}.$$

Similarly, for checking the side condition of the rule $\mathbf{R}_{\mathcal{H}}$, for each role R occurring in \mathcal{O} , we store the sets of its sub-roles and super-roles:

$$R.\text{superRoles} = \{S \mid R \sqsubseteq_{\mathcal{O}}^* S\},$$
$$R.\text{subRoles} = \{S \mid S \sqsubseteq_{\mathcal{O}}^* R\}.$$

The computation of the index is usually quick and can be done concurrently.

To identify relevant premises from the set of processed axioms for the context associated with C , we store the processed axioms for this context in three records according to the cases by which these axioms were assigned to C in Algorithm 5:

$$C.\text{subsumptions} = \{D \mid C \sqsubseteq D \in \text{processed}\},$$
$$C.\text{predecessors} = \{\langle R, D \rangle \mid D \sqsubseteq \exists R.C \in \text{processed}\},$$
$$C.\text{implications} = \{\langle R, E \rangle \mid \exists R.C \rightarrow E \in \text{processed}\}.$$

The pairs in the last two records are indexed by the key R , so that for every role R one can quickly find all concepts D and, respectively, E that occur in the pairs with R . Given this indexed data structure, the function deriving conclusions within a context C can be described by Algorithm 6. Note that the algorithm extensively uses iterations over intersections of two sets; optimizing such iterations is essential for achieving efficiency of the algorithm.

6 Experimental Evaluation

To evaluate our approach, we have implemented the procedure in the Java-based reasoner ELK using lock-free data structures, such as `ConcurrentLinkedQueue`,

Algorithm 6: deriveConclusions(processed, axiom) for context C

```
1 result  $\leftarrow \emptyset$ ;  
2 if axiom match  $C \sqsubseteq D$  then  
3   for  $D_1 \in (C.\text{subsumptions} \cap D.\text{leftConjuncts})$  do  
4      $\lfloor$  result.add( $C \sqsubseteq D_1 \sqcap D$ ); // rule  $R_{\sqcap}^+$ , right premise  
5   for  $D_2 \in (C.\text{subsumptions} \cap D.\text{rightConjuncts})$  do  
6      $\lfloor$  result.add( $C \sqsubseteq D \sqcap D_2$ ); // rule  $R_{\sqcap}^+$ , left premise  
7   // similarly for rules  $R_{\sqsubseteq}^-$ ,  $R_{\sqcap}^-$ ,  $R_{\exists}^-$ ,  $R_{\top}^+$ ,  $R_{\exists}^+$   
8 if axiom match  $D \sqsubseteq \exists R.C$  then  
9   for  $S \in (C.\text{implications.keySet}() \cap R.\text{superRoles})$  do  
10    for  $E \in C.\text{implications.get}(S)$  do  
11      $\lfloor$  result.add( $D \sqsubseteq E$ ); // rule  $R_{\mathcal{H}}$ , left premise  
12    // similarly for rule  $R_{\mathcal{T}}$ , left premise  
13 if axiom match  $\exists S.C \rightarrow E$  then  
14   for  $R \in (C.\text{predecessors.keySet}() \cap S.\text{subRoles})$  do  
15    for  $D \in C.\text{predecessors.get}(R)$  do  
16      $\lfloor$  result.add( $D \sqsubseteq E$ ); // rule  $R_{\mathcal{H}}$ , right premise  
17    // similarly for rule  $R_{\mathcal{T}}$ , right premise  
18 return result;
```

and objects such as AtomicBoolean, which allow for ‘compare-and-swap’ operations, provided by the `java.util.concurrent` package.¹ The goal of this section is (a) to compare the performance of ELK in practical situations with other popular reasoners, and (b) to study the extent in which concurrent processing contributes to the improved classification performance. To evaluate (a) we have used a notebook with Intel Core i7-2630QM 2GHz quad core CPU and 6GB of RAM, running Microsoft Windows 7 (experimental configuration ‘laptop’). To evaluate (b) we have additionally used a server-type computer with an Intel Xeon E5540 2.53GHz quad core CPU and 24GB of RAM running Linux 2.6.16 (experimental configuration ‘server’). In both configurations we ran Java 1.6 with 4GB of heap space. All figures reported here were obtained as the average over 10 runs of the respective experiments.

Our test ontology suite includes SNOMED CT, GO, FMA-lite, and an OWL EL version of GALEN.² The first part of Table 3 provides some general statistics about the sizes of these ontologies. We have measured performance on these ontologies for the reasoners CB r.12 [7], FaCT++ 1.5.2 [17], jCEL 0.15.0,³ and Snorocket 1.3.0 [9]. We selected these tools as they provide specific support for

¹ The reasoner is available open source from <http://code.google.com/p/elk-reasoner/>

² SNOMED CT from <http://ihtsdo.org/> (needs registration); GO from <http://lat.inf.tu-dresden.de/~meng/toyont.html>, FMA-lite from <http://www.bioontology.org/wiki/index.php/FMAInOwl>, GALEN from <http://condor-reasoner.googlecode.com/>

³ <http://jcel.sourceforge.net/>

Table 3. Statistics for studied ontologies and classification times on ‘laptop’ for commonly used \mathcal{EL} reasoners and ELK; times are in seconds; timeout was 1 hour

	SNOMED CT	GALEN	FMA	GO
#concepts	315,489	23,136	78,977	19,468
#roles	58	950	7	1
#axioms	430,844	36,547	121,712	28,897
CB	13.9	1.4	0.7	0.1
FaCT++	387.1	timeout	5.4	7.5
jCEL	661.6	32.5	12.4	2.9
Snorocket	23.2	unsupported	1.6	0.3
ELK (1 worker)	13.15	1.33	0.44	0.20
ELK (2 workers)	7.65	0.90	0.38	0.18
ELK (3 workers)	5.66	0.80	0.39	0.19
ELK (4 workers)	5.02	0.77	0.39	0.19

\mathcal{EL} -type ontologies. The second part of Table 3 shows the time needed by the tested reasoners to classify the given ontologies in the ‘laptop’ scenario. The times are as the reasoners report for the classification stage, which does not include the loading times. The last part of Table 3 present the result for ELK tested under the same conditions for a varying number of workers. As can be seen from these results, ELK demonstrates a highly competitive performance already for 1 worker, and adding more workers can substantially improve the classification times for SNOMED CT and GALEN.

The results in Table 3 confirm that concurrent processing can offer improvements for ontology classification on common computing hardware. On the other hand, the experiments demonstrate that the improvement degrades with the number of workers. There can be many causes for this effect, such as dynamic CPU clocking, shared Java memory management and garbage collection, hardware bottlenecks in CPU caches or data transfer, and low-level mechanisms like Hyper-Threading. To check to what extent the overhead of managing the workers can contribute to this effect, we have performed a series of further experiments.

First, we have checked if adding more workers than the number of available cores would cause a slow down. The left part of Fig. 2 shows the results for GALEN obtained for 1 – 8 workers on ‘laptop’ and ‘server’ configurations. The reported data is classification time (left axis) and speedup, i.e., the quotient of single worker classification time by measured multi-worker classification time (right axis). The ideal linear speedup is indicated by a dotted line. As can be seen from the results, there is no significant change in the classification times for more than 4 workers, and the classification times for the server can even slightly improve (probably due to Hyper-Threading). Similar results can be seen for SNOMED CT in the right part of Fig. 2. Again, we can see a clear gain between 1–4 workers, and a less pronounced gain for 5–8 workers. It is interesting to note that the server configuration achieves better speedups on GALEN, whereas the laptop configuration achieves better speedups on SNOMED CT. This illustrates

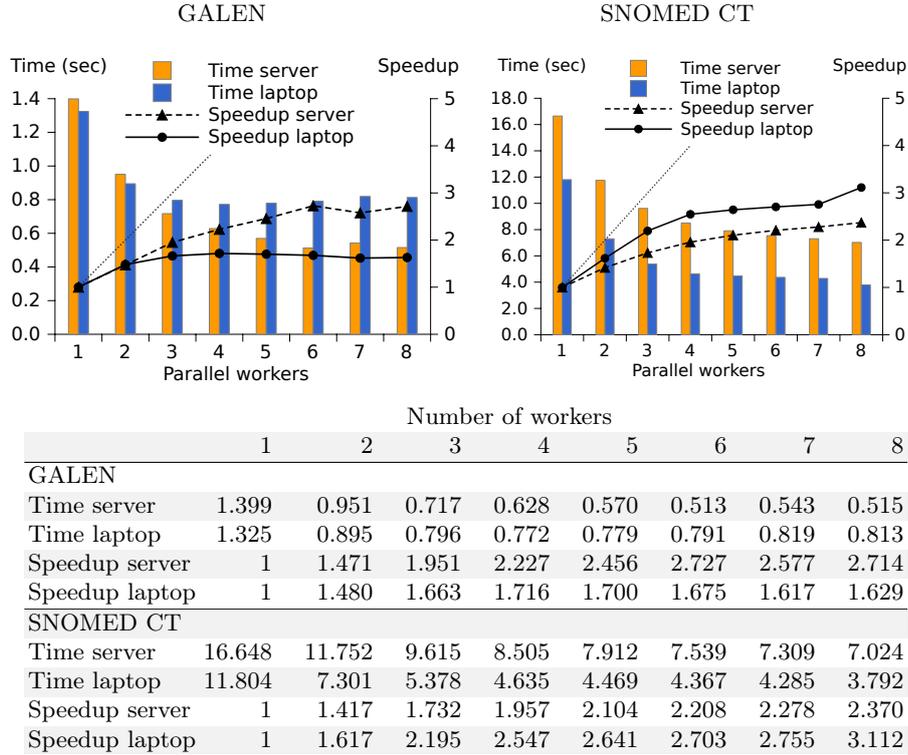


Fig. 2. Classification time and speedup for n workers on GALEN and SNOMED CT

that hardware configurations may have a complex effect on the performance of concurrent applications.

Next, we measured how our procedure would score against the ‘embarrassingly parallel’ algorithm in the situation when an ontology consists of n disjoint and equal copies, which can be classified completely independently. We have created ontologies consisting of n disjoint copies of our test ontologies, and ran n independent ELK reasoners with 1 worker on these n copies. We compared the average classification times of this pre-partitioning approach with the times needed by ELK when using n workers on the union of these partitions. Both approaches compute exactly the same results.

The results of this experiment for copies of GALEN are presented in Fig. 3. As can be seen from these results, the classification times for both scenarios grows with n (ideally, it should remain constant up to $n = 4$), but, what is more important, the difference between the two approaches is not considerable. We interpret the additional time used by our concurrent implementation as the overhead of managing concurrent computations. Especially the performance impact of syntactically unrelated axioms from disjoint copies is very small due to the indexing strategies discussed in Section 5. The fact that pre-partitioning re-

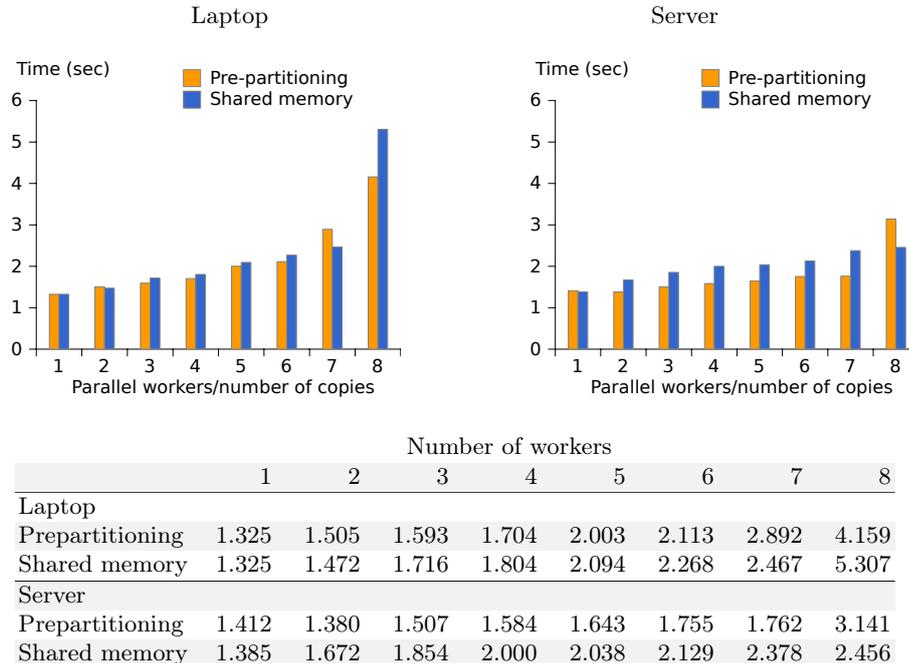


Fig. 3. Classification time for n workers on n copies of GALEN

quires additional time for initial analysis and rarely leads to perfect partitioning [16] suggests that our approach is more suitable for the (single machine, shared memory) scenario that we target.

7 Related Works and Conclusion

To the best of our knowledge, we have presented one of the first practical algorithms for concurrent terminological reasoning in a fragment of OWL. There are only a few previous works on concurrent OWL reasoning. Notable approaches include an early work on parallel application of (incomplete) structural reasoning algorithms [4], a tableaux procedure that concurrently explored non-deterministic choices [10], a resolution calculus for *ALCHIQ* where inferences are exchanged between distributed workers [14], and a distributed classification algorithm that can be used to concurrently invoke (serial) OWL reasoners for checking relevant subsumptions [1]. Experimental evaluations in each case indicated potential on selected examples, but further implementation and evaluation will be needed to demonstrate a clear performance advantage of these systems over state-of-the-art systems.

Some other works have studied concurrency in light-weight ontology languages. Closest to our approach is a distributed MapReduce-based algorithm for \mathcal{EL}^+ [13]. However, this idea has not been evaluated in practice. Works dedicated

to OWL RL [12] include an approach for pre-partitioning inputs that inspired the evaluation in Section 6 [16], and recent MapReduce approaches [6,18].

Many further works focus on the distribution of reasoning with assertional data using weaker schema-level modelling languages pD^* (a.k.a. OWL-Horst) and (fragments of) RDFS [5,19,20,8]. These works are distinguished from our approach by their goal to manage large-scale data (in the range of billions of axioms), which is beyond the memory capacity of single machines. Accordingly, computation is distributed to many servers without sharing memory. Yet, we can find similarities in term-based distribution strategies [5,19,20,6,18,13] and indexing of rules [6] with our strategy of assigning contexts to axioms.

In conclusion, we can say that this work does indeed appear to be the first to demonstrate a compelling performance advantage for terminological reasoning in OWL through exploiting shared-memory parallelism on modern multi-core systems. We hope that these encouraging results will inspire further works in this area, by utilizing the potential of the existing general ideas, such as MapReduce, on the one hand, and by developing new approaches for parallelization specific to OWL reasoning techniques, such as consequence-based reasoning, on the other hand.

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