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ON THE LEARNING OF MULTIPLE CONCEPTS IN
DESCRIPTION LOGIC

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MAIO DE 2014

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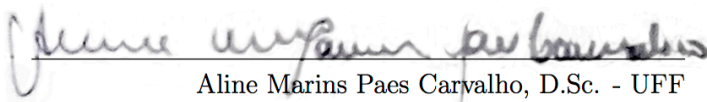
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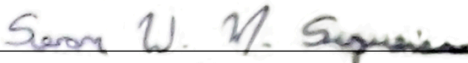
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Resumo

Linguagens baseadas em Lógicas de Descrição são comumente adotadas como o esquema padrão para a representação de conhecimento em ontologias. Tipicamente, uma ontologia formaliza um número de conceitos dependentes e relacionados de um domínio, agrupados como uma terminologia. Como a definição manual de tais terminologias é complexa, consome tempo e ainda é passível de erros, existe um grande interesse e demanda por métodos automáticos de aprendizado de terminologias. No entanto, as abordagens existentes seguem uma estratégia de aprendizado de um único conceito, desconsiderando dependências que possam existir entre conceitos. Como consequência, são induzidas terminologias mais complexas e por vezes ilegíveis. Logo, métodos para o aprendizado de vários conceitos dentro de uma tarefa, respeitando suas dependências são essenciais para a indução automática de ontologias compactas e compreensíveis. Assim, neste trabalho, propomos três estratégias para o aprendizado de terminologias compostas por múltiplos conceitos relacionados. Nós empiricamente avaliamos com sucesso todas as três em dois *benchmarks* e as comparamos com um algoritmo padrão de aprendizado de conceitos únicos.

Palavras-chave: Aprendizado de Múltiplos Conceitos em Lógicas de Descrição, Aprendizado de Terminologias, Remoção de Redundâncias em Lógicas de Descrição, Compressão de Terminologias, Restruturação de Teorias.

Abstract

Description Logics based languages have emerged as the standard knowledge representation scheme for ontologies. Typically, an ontology formalizes a number of dependent and related concepts in a domain, encompassed as a terminology. As manually defining such terminologies is a complex, time consuming and error-prone task, there is great interest and even demands for methods that learn terminologies automatically. However, the existing approaches follow a single concept learning strategy, disregarding dependencies that may exist among the concepts. As a consequence, a more complex and sometimes illegible terminology may be induced. Thus, methods for learning all the concepts within an unique task, respecting their dependency are essential for automatically inducing compact and understandable ontologies. Then, in this work, we propose three strategies for learning a terminology composed of multiple related concepts. We empirically evaluated successfully all of them in two benchmarks and compared them with a standard single concept learning algorithm.

Keywords: Multiple Concept Learning in Description Logics, Terminology Learning, Redundancy Removal on Description Logics, Terminology Compression, Theory Restructure.

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1 INTRODUCTION

The original intention for the World Wide Web was to provide a distributed collection of documents, connected via Hyperlinks accessible via the Internet. As it is, the unstructured nature of the information on the Web, although easily accessible by humans, provides a challenge for machines to efficiently analyse it. Berners-Lee et al. (2001) proposes a road map to transform the web from a machine hostile environment into a place where machine reasoning can be “ubiquitous and devastatingly powerful”. This set of ideas is called as *Semantic Web*.

There are two major challenges to Semantic Web’s usage: i) a standard knowledge representation formalism and ii) the lack of structured knowledge.

Knowledge representation (Brachman and Levesque, 2004) is an important task when considering applications that require reasoning over a domain. In order for the machines to be capable of analysing the information available on the Web, the information must be structured. *Ontologies* (Staab and Studer, 2010) are formally defined knowledge bases, and as such they provide the needed structure for the information on the Semantic Web. *OWL Web Ontology Language* (OWL)¹ has become a W3C Recommendation in February 2004 and is the current standard for defining ontologies to the Semantic Web. Since 2012² it is comprised of six profiles with varying expressiveness. The six profiles are: OWL 2 RDF-Based Semantics, OWL 2 Direct Semantics, OWL 2 EL, OWL 2 QL, OWL 2 RL and OWL 1 DL. Its vocabulary can be directly related to the formal semantics of Description Logics

¹<http://www.w3.org/TR/owl-features/>

²<http://www.w3.org/TR/owl2-profiles/>

(DLs) (Baader and Nutt, 2010).

DLs form a family of representational languages, with different expressive power, that are typically decidable fragments of first order logic (FOL) (Huth and Ryan, 2004). They represent domain concepts and relations between them.

The lack of readily available ontologies indicates the need for applications that support the creation and maintenance of them, using existing background knowledge. One way to resolve this challenge is to manually define DL ontologies (also known as knowledge bases - \mathcal{KB}), however this process is time consuming and still error prone. Therefore, the consideration of mechanisms for automatically learning (Anderson et al., 1986) a model represented in DL is relevant and sometimes even demanded. A number of approaches have been proposed in the literature, such as the algorithms proposed in (Lehmann and Hitzler, 2010), (Fanizzi et al., 2008) and (Iannone et al., 2007). These algorithms are used to learn the terminological part of a DL ontology, also known as TBox. Terminologies are used to describe the concepts of a domain and their relations. However, to the best of our knowledge, the description logic learning approaches devised so far follow a single learning strategy, i.e., focus on learning piecewise concepts. When learning multiple concepts, independent executions of the learning algorithm are performed for each one of the concepts, thus the information regarding dependencies among them is lost. We argue that when the several concepts belonging to a DL are learned jointly, the final terminologies may be more compact, and therefore more useful. Moreover, learning jointly the concepts may yield more accurate concepts than usual approaches, since each concept may have in its definition others concepts previously defined, as a starting point. A relationship of dependency between two concepts occurs when a concept definition uses another concept. For example, concept C depends on concept D if D appears in C's definition. Thus, in this work we investigate the following hypothesis:

If dependencies among the concepts of the domain that need to be learned are found then clearer and compact terminologies are produced,

while their quality is maintained.

In this hypothesis, “quality” refers to the predictive power of the terminology.

1.1 GOALS

In this work, we present three alternatives for identifying concept dependencies among the group of concept that will be learned, aiming at finding clearer terminologies through their dependencies. These methods are the main contributions of this work. Next, we briefly introduce them.

1.1.1 CONCEPT DEPENDENCY THROUGH EXAMPLES

Concept Dependency through Examples’s (CDE) (Melo et al., 2013b) solution devises a learning order suitable for finding dependencies among the group of concepts that will be learned. The learning order is extracted from a taxonomy built from the learning tasks examples. The intersection between sets of examples indicates a relationship between the concepts, based on this the taxonomy models the *subsumer/subsumee* relationship between concepts.

A learning order may yield terminologies with dependencies among the learned concepts because the concepts learned in an iteration can utilize concepts defined in previous iterations.

Because of the way the taxonomy is built and traversed to extract the learning order, CDE has a preference to express dependencies using conjunctions.

1.1.2 CONCEPT DEPENDENCY THROUGH ASSERTIONS

The second method, *Concept Dependency through Assertions’s* (CDA) (Melo et al., 2013a)³ allows the use of concepts not yet defined, in the form of assertions, during the learning of other concepts, thus enabling the discovery of dependencies.

These assertions are used as surrogates for the latter found definitions. They are created based on the learning task’s examples, and latter added into the background knowledge as facts that can be used while learning other concepts. The use of

³Named MCL on its first appearance.

these assertions allows for a greater diversity in the types of ways to express the dependencies among the concepts, w.r.t. those found by CDE.

1.1.3 CONCEPT DEPENDENCY THROUGH TERMINOLOGY

Concept Dependency through Terminology's (CDT) (Melo et al., 2014)⁴ identifies dependencies by finding redundancies within a terminology. A redundancy is characterized when a section within a concept definition is equivalent to the full definition of another concept. The substitution of a section by its equivalent concept yields a smaller terminology while maintaining the same semantics. This method can be applied *after* a terminology is obtained, be it via a manual definition of a terminology learning task, hence its name.

The three proposed methods were implemented as packages using the programming language Java and are available at <https://github.com/raphael-melo/mcl>.

An experimental evaluation was conducted comparing the three approaches. Moreover, we compared them to DL-Learner (Lehmann and Hitzler, 2010), a framework that performs single concept learning tasks, showing the benefits of a multiple concept learning algorithm over a single concept learning algorithm.

1.2 ORGANIZATION

This master dissertation is organized as follows. Chapter 2 presents the background knowledge necessary to understand the proposed approaches. In Chapter 3, our three approaches for multiple concept learning are described in detail. Chapter 4 presents the experiments conducted to validate our proposals. Chapter 5 presents the works related to this research. Finally, Chapter 6 presents the closing remarks of this research, a summary of the contributions and directions for future work.

⁴Called Redundancy Removal on DLs Descriptions (R2D2) on its first appearance.

2 BACKGROUND KNOWLEDGE

In this chapter we present the background knowledge necessary to understand this work. First we present the foundations of *Description Logics*, discussing its syntax and semantics. A firm grasp of DLs is necessary to fully understand the proposed methods.

Secondly we present the problem of learning a concept definition. First the ideas of *Inductive Logic Programming* are shown, because it provides the bases for concept learning in Description Logics, defined just after.

Lastly, we present formal arguments supporting the motivation for methods that simplify terminologies and the relationship between simplicity and understandability.

2.1 DESCRIPTION LOGICS

Description Logics (DL) (Baader and Nutt, 2010) is the name given for a family of knowledge base representation (KR) formalisms used to represent domain knowledge by defining a terminology (the relevant concepts in the domain), then using these concepts to describe properties of individuals in the domain. The terminology and the information about the individuals form the knowledge base (\mathcal{KB}). Description Logics contains a formal logic-based semantics, hence its name. DLs are also characterized by its focus on reasoning as a service: allows the inference of implicit knowledge from the explicit knowledge contained in the knowledge base (\mathcal{KB}). It has two reasoning services: i) classification of concepts and ii) classification of individuals. The classification of concepts determines subconcept-superconcept relationships

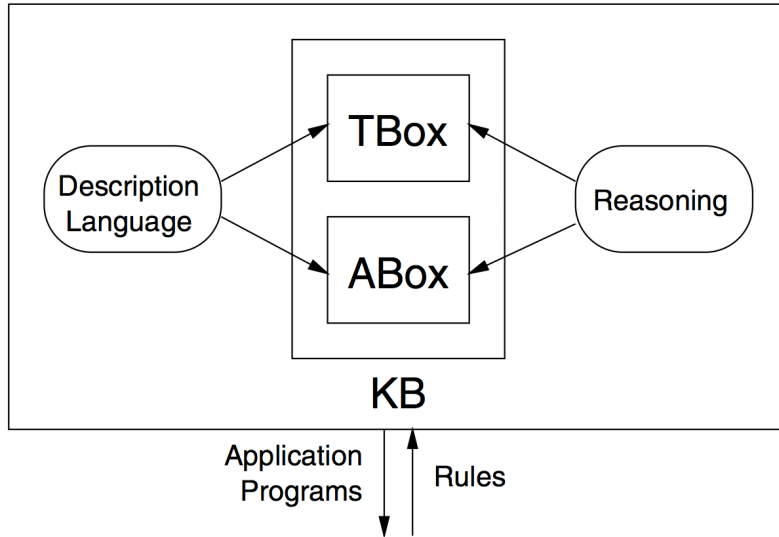


Figure 2.1: Architecture of a knowledge representation system based on Description Logics (Baader and Nutt, 2010).

between them (also called subsumption relationship in DL). The classification of individuals determines, based on the properties of the individual, whether it is an instance of a certain concept.

Description Logics are useful for Semantic Web because, unlike *First Order Logic* (FOL) theories, they are decidable, i.e., a query is always answered, either positive or negatively. However, the *decidability* and *complexity* depends on the Description Logic language chosen. There is a tradeoff between expressiveness and the reasoning complexity. A higher expressive power incurs in a higher reasoning complexity, on the other hand, a lower expressive power incurs in a lower reasoning complexity.

A *Knowledge Base* (\mathcal{KB}) has two components: a *TBox* and a *ABox*. The TBox contains the *terminology*, i.e., the domain's vocabulary, while the *ABox* contains assertions about the individuals using the terms defined in the terminology. Fig. 2.1 displays the architecture of a knowledge representation system based on Description Logics.

Atomic concepts and *roles* are the elementary descriptions. Complex descriptions, or *descriptions* in short form, can be built from them using concept *constructors*. DLs languages are distinguished by the set of constructors they provide, therefore the expressiveness of a DL is tied to its set of constructors. In the re-

Table 2.1: Syntax and Semantics for DL's Constructors. (Calvanese, 1996)

Constructor's Name		Syntax	Semantics
atomic concept		A	$A^{\mathcal{I}} \subseteq \mathcal{D}^{\mathcal{I}}$
universal concept		\top	$\mathcal{D}^{\mathcal{I}}$
bottom concept		\perp	\emptyset
atomic negation		$\neg A$	$\mathcal{D}^{\mathcal{I}} / A^{\mathcal{I}}$
intersection		$C \sqcap D$	$C^{\mathcal{I}} \cap D^{\mathcal{I}}$
value restriction		$\forall R.C$	$\{o \forall o' : (o, o') \in R^{\mathcal{I}} \rightarrow o' \in C^{\mathcal{I}}\}$
limited existential quantification		$\exists R$	$\{o \exists o' : (o, o') \in R^{\mathcal{I}}\}$
existential quantification	\mathcal{E}	$\exists R.C$	$\{o \exists o' : (o, o') \in R^{\mathcal{I}} \wedge o' \in C^{\mathcal{I}}\}$
disjunction	\mathcal{U}	$C \sqcup D$	$C_1^{\mathcal{I}} \cup D_2^{\mathcal{I}}$
general negation	\mathcal{C}	$\neg C$	$\mathcal{D}^{\mathcal{I}} \setminus C^{\mathcal{I}}$
qualified number restrictions	\mathcal{Q}	$\exists^{\geq m} R$	$\{o \#\{o' (o, o') \in R^{\mathcal{I}}\} \geq m\}$
		$\exists^{\leq n} R$	$\{o \#\{o' (o, o') \in R^{\mathcal{I}}\} \leq n\}$
well-founded	\mathcal{W}	$wf(R)$	$\{o_0 \forall o_1, o_2, \dots (\text{ad infinitum}) \exists i \geq 0 : (o_i, o_{i+1}) \notin R^{\mathcal{I}}\}$
role value map	\mathcal{V}	$R_1 \subseteq R_2$	$\{o \{o' (o, o') \in R_1^{\mathcal{I}}\} \subseteq \{o' (o, o') \in R_2^{\mathcal{I}}\}\}$
role name		R	$R^{\mathcal{I}} \subseteq \mathcal{D}^{\mathcal{I}} \times \mathcal{D}^{\mathcal{I}}$
inverse	\mathcal{I}	R^{-}	$\{(o, o') (o', o) \in R^{\mathcal{I}}\}$
union	\mathcal{R}	$R_1 \cup R_2$	$R_1^{\mathcal{I}} \cup R_2^{\mathcal{I}}$
concatenation	\mathcal{R}	$R_1 \circ R_2$	$R_1^{\mathcal{I}} \circ R_2^{\mathcal{I}}$
reflexive transitive closure	\mathcal{R}	R^*	$(R^{\mathcal{I}})^*$
identity	\mathcal{R}	$id(C)$	$\{(o, o) o \in C^{\mathcal{I}}\}$
difference	\mathcal{D}	$R_1 \setminus R_2$	$R_1^{\mathcal{I}} \setminus R_2^{\mathcal{I}}$

mainder of this work we use the letters a, b, a_1, b_1, \dots for *individuals*; the letters A, B, A_1, B_1, \dots for *atomic concepts*, the letters R, R_1, \dots for *atomic roles* and the letters C, D, C_1, D_1, \dots for *concept descriptions*. An *assertion* has the form $C(a)$ (*concept assertion*) or $R(a, b)$ (*role assertion*),

Table 2.1 displays the syntax and semantics for various DL constructors. The first column specifies the constructor's name. The second column specifies the letter that denote the constructor when naming the logic. The syntax of each constructor is given in the third column.

The language \mathcal{AL} - Attributive Language (Schmidt-Schauss and Smolka, 1991) is the minimal DL language. Its constructors are the set within Table 2.1 with no

KB	
TBox	ABox
Father \equiv Male \sqcap \exists Parent. \top	Male(ALFRED)
Mother \equiv Female \sqcap \exists Parent. \top	Male(CARL)
Wife \equiv Female \sqcap \exists Married.Male	Female(BEATRICE)
Husband \equiv Male \sqcap \exists Married.Female	Female(CORNELIA)
	Parent(BEATRICE, CORNELIA)
	Parent(ALFRED, CORNELIA)
	Father(ALFRED)
	Mother(CORNELIA)
	Married(CARL, BEATRICE)
	Married(BEATRICE, CARL)

Figure 2.2: Example of a DL Knowledge Base using the language \mathcal{AL} .

letter associated. The other DL languages are extensions of \mathcal{AL} . Example 1 shows how a definition in natural language can be translated into a concept description using the language \mathcal{AL} , while Fig. 2.2 shows an example of a complete \mathcal{KB} .

Example 1. *Let the natural language definition for the “Father” concept, in the kinship domain, be:*

“Father is a male parent”; one can define its concept description as:

$$\text{Father} \equiv \text{male} \sqcap \exists \text{Parent}.\top$$

The forth column of Table 2.1 displays the semantics for the constructors. The semantics of a description is given by a *domain* \mathcal{D} (a set) and an *interpretation* \mathcal{I} (a functor). Individuals represent individuals through names from a set $N_I = \{a, b, \dots\}$. Each *concept* in the set $N_C = \{A, B, C, D, A_1, B_1, \dots\}$ is interpreted as a subset of a domain \mathcal{D} (Example 2). Each *role* in the set $N_R = \{R, R_1, \dots\}$ is interpreted as a binary relation on the domain (Example 3).

Example 2. *The interpretation of the concept “Male”, based on the \mathcal{KB} present in Figure 2.2, is the following:*

$$\text{Male}^{\mathcal{I}} = \{\text{ALFRED}, \text{CARL}\}$$

Example 3. *The interpretation of the role “Married”, based on the \mathcal{KB} present in Figure 2.2, is the following:*

$$\text{Married}^{\mathcal{I}} = \{(CARL, BEATRICE), (BEATRICE, CARL)\}$$

An interpretation \mathcal{I} *satisfies* an *inclusion axiom* $C \sqsubseteq D$ if $C^{\mathcal{I}} \sqsubseteq D^{\mathcal{I}}$, and it satisfies an *equality axiom* $C \equiv E$ if $C^{\mathcal{I}} = E^{\mathcal{I}}$. An interpretation that satisfies all axioms in a terminology \mathcal{T} is called a *model* of \mathcal{T} . A *finite model* is a model with finite domain. A concept description C is (finitely) *consistent* in \mathcal{T} if \mathcal{T} admits a (finite) model \mathcal{I} such that $C^{\mathcal{I}} \neq \emptyset$ and C is (finitely) *subsumed* by D in \mathcal{T} if $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$ for every (finite) model \mathcal{I} of \mathcal{T} (Calvanese, 1996).

Moreover, in this master dissertation, we assume the common assumption made about DL terminologies: (i) there is only one definition for a concept name and (ii) concept definitions are acyclic.

2.2 INDUCTIVE LOGIC PROGRAMMING (ILP)

Modeling the knowledge of a domain is an essential task in computer and information science. However, manually formalizing the domain knowledge is an expensive and still an error prone task, even more because the domain experts themselves do not always agree about definitions and their relationships (Maedche and Staab, 2001). Therefore, in order to effectively exploit such terminologies it is necessary to apply techniques from machine learning (Mitchell, 1997) for automatically inducing terminologies from data.

Inductive Logic Programming (ILP) is a research field in the intersection of machine learning and logic programming (Lavrac and Dzeroski, 1994; Muggleton and De Raedt, 1994). ILP research has the goal of finding learning algorithms for inducing logic programs that represents relational definitions.

Logic Programming is a programming paradigm based on formal logic. It uses a strict form of First-Order Logic (FOL) theories, where *sentences* can only be *clauses* (disjunction of *literals*¹) with at most one positive literal. These types of clauses are

¹A literal is a predicate or the negation of a predicate.

known as *Horn Clauses* (Horn, 1951).

A Horn Clause with exactly one positive literal is called a *definite clause*. A definite clause with no negative literal is called a *fact*. A Horn Clause with no positive literal is called a *goal clause*.

Formally defined logical theories are useful because of the ability to infer new implicit knowledge that follows from the explicit background knowledge \mathcal{BK} (*inferential reasoning*). The rules of inference defines that given a sentence (or a set of sentences) with certain properties a sentence (or a set of sentences) can be derived as a conclusion. A rule is *sound* when it preserves the truth-value for any interpretation, a rule is also *complete* if every logically valid sentence is derivable. The inference of new information is done through a set of sound *inference rules*.

The *Resolution rule* was presented by Robinson (1965). Resolution is a valid inference rule (sound and complete), that can, without any other inference rule, be used to build a sound and complete theorem proving method. Iteratively applying the resolution rule in a proper way allows for finding if a FOL clause is satisfiable.

Horn Clauses are important because their properties² leads to an efficient theorem proving method (Dowling and Gallier, 1984).

ILP methods has as goal to find a hypothesis \mathcal{H} that best defines a given set of positive and negative examples taking into account a background knowledge (\mathcal{BK}) (Definition 1). The hypothesis, \mathcal{BK} and examples are logical programs.

Definition 1 (Concept Learning in ILP (Muggleton and De Raedt, 1994)). *Given:*

- a base theory \mathcal{BK} (a logical program with Horn clauses);
- a set of positive examples \mathcal{E}^+ ;
- a set of negative examples \mathcal{E}^- ;

Find a logical program \mathcal{H} on which the following conditions hold:

- every positive example $e \in \mathcal{E}^+$ is covered by $\mathcal{H} \wedge \mathcal{BK}$ (complete);

²The resolvent of two Horn Clauses is itself a Horn Clause; the resolvent of a goal clause and a definite clause is a goal clause.

- *no negative example $e \in \mathcal{E}^-$ is covered by $\mathcal{H} \wedge \mathcal{BK}$ (consistent).*

An example is covered by a logical program \mathcal{H} if it can be logically inferred from it.

The problem of solving a ILP learning task can be regarded as a search problem, where the space of solutions are: (i) the “well formed” set of hypotheses and (ii) a acceptance criterion for the candidate hypotheses³.

2.3 CONCEPT LEARNING IN DESCRIPTION LOGICS

Since concepts are the basic components of terminologies, the first attempt on machine learning would be how to learn a concept definition from available data. This is called *Concept Learning in Description Logics*, henceforth *Concept Learning* (CL). A number of algorithms together with implementations have been proposed in the literature (Lehmann and Hitzler, 2010; Fanizzi et al., 2008; Lehmann, 2009; Iannone et al., 2007). Concept Learning and ILP have a similar relationship as DL and Logical Programming, respectively. As such Concept Learning research has been heavily influenced by the developments within ILP.

When learning a concept, one has as goal of finding a generalized and correct definition of such a concept from a set of examples, as defined below:

Definition 2 (Concept Learning). $CL(C_T, \mathcal{E}, \mathcal{KB})$ or CL_{C_T} for short.

Given:

- *a knowledge base \mathcal{KB} ;*
- *a target concept C_T such as $C_T \notin \mathcal{KB}$;*
- *a set of target examples \mathcal{E} , typically divided into positive (\mathcal{E}_p) and negative (\mathcal{E}_n) examples, such that $\mathcal{E} = \mathcal{E}_p \cup \mathcal{E}_n$*

Find a definition C for the concept C_T such that:

- $\mathcal{KB} \cup C \models \mathcal{E}_p$ (complete);

³Along with coverage, parsimony is also a goal, i.e., smaller theories are preferable.

- $\mathcal{KB} \cup C \not\models \mathcal{E}_n(\text{consistent})$;
- $C_T \in C_{T_S}$ ⁴, $C_{T_S} = \{C_T, C_{T_1}, \dots, C_{T_n}\}$, $\text{length}(C_T) \leq \text{length}(C_{T_i})$ for $i = 1, \dots, n$ (*parsimony*)⁵

Definition 3 (Length). *Length is the sum of all constructors and concepts presented in a concept definition after the equivalence symbol (\equiv), e.g., $A \equiv B \sqcap C \sqcap D$ has a length of 5.*

Definition 4 follows if a concept definition found is both *complete* and *consistent*.

Definition 4 (Consistency between adding examples and concept definition). *If definition C for the target concept C_T , with the set of examples $\mathcal{E}_T = \mathcal{E}_{T_p} \cup \mathcal{E}_{T_n}$, is found, then $\mathcal{KB} \cup C \cup \mathcal{E}_{T_p} \cup \mathcal{E}_{T_n}$ is consistent and semantically equal to $\mathcal{KB} \cup C$*

An algorithm for concept learning is usually composed of the following elements (Lehmann and Hitzler, 2010)

- **a refinement operator** that builds the search tree of concepts;
- **a search algorithm** that controls how this search tree is traversed;
- **a scoring function** that evaluates the nodes of the tree and to point out the best current concept candidate.

The refinement operator allows one to find candidate concept definitions through two basic tasks: generalization and specialization (Lehmann and Hitzler, 2008a). Such operators in both ILP and description logic learning rely on subsumption to establish an ordering so as to traverse the search space. If a concept C subsumes a concept D ($D \sqsubseteq C$), then C covers all examples which are covered by D , which makes subsumption a suitable order. Arguably the best refinement operator for description logic learning is the one available in the DL-Learner system (Lehmann and Hitzler, 2008a, 2010).

⁴The set of possible solutions.

⁵Within Concept Learning this is viewed as a general goal more than as a requirement.

In a deterministic setting, a covering relationship simply tests whether, for given candidate concept definition (C), a given example e holds; that is, $\mathcal{KB} \cup C \models e$ where $e \in \mathcal{E}_p$ or $e \in \mathcal{E}_n$. In this sense, a cover relationship $\text{cover}(e, \mathcal{KB}, C)$ indicates whether a candidate concept covers a given example (Fanizzi et al., 2008). In DL learning, one often compares candidates through scoring functions based on the number of positive/negative examples covered. In DL-Learner a fitness relationship considers the number of positive examples and negative examples covered as well as the length of solutions when expanding candidates in the tree search.

The learning algorithm depends basically on the way we traverse the candidate concepts obtained after applying refinement operators. In a deterministic setting the search for candidate concepts is often based on the FOIL (Quinlan and Cameron-Jones, 1993) algorithm. There are also different approaches (for instance, DL-Learner, an approach based on genetic algorithms (Lehmann, 2007), and one that relies on horizontal expansion and redundancy checking to traverse search trees (Lehmann and Hitzler, 2008b)).

The refinement operator is responsible for generating candidate definitions for the target concept. Candidate definitions are generated by joining DL’s constructors, concepts and roles available in the \mathcal{KB} , this is illustrated in Example 4.

Example 4. *Let \mathcal{KB} be as presented in Figure 2.2 and the concept learning task be $CL(\text{SINGLEFATHER}, \mathcal{E}_{SF}, \mathcal{KB})$. The \mathcal{E}_{SF} is composed of $\mathcal{E}_P = \{\text{ALFRED}\}$ and $\mathcal{E}_N = \{\text{BEATRICE}, \text{CARL}\}$. A sound concept definition found could be $\text{SINGLEFATHER} \equiv \text{Father} \sqcap \forall \text{Married}.\perp$.*

Figure 2.3 depicts the tree of candidates definitions.

2.4 MODEL’S SIMPLICITY AND HOW IT AFFECTS ITS UNDERSTANDABILITY

Historically simplicity has been a hallmark of philosophical and later scientific descriptions. Occam’s razor⁶, or *Lex Parsimoniae* is a logical principle taken as a

⁶Johannes Poncius is the 17th scholar responsible for the classical formulation

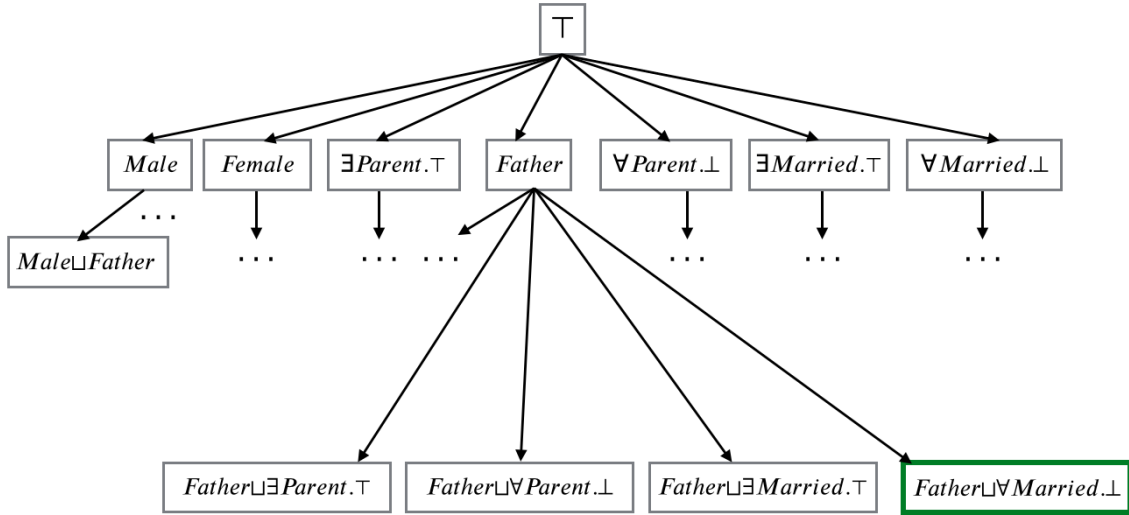


Figure 2.3: Example of a search tree constructed to create candidates definitions.

tenet of the modern philosophy of science. Aristotle’s *Posterior Analytics* /refaristotle:posteriorAnalytics summarizes the parsimony principle:

“We may assume the superiority *ceteris paribus* (all things being equal) of the demonstration which derives from fewer postulates or hypotheses.”

The parsimony principle is a way to choose between competing hypotheses. In principle, the parsimony’s primacy cannot be empirically proved. However, it is built upon an intuition on the nature of reality.

The ideas proposed in the philosophy of science are used to create machine learning methods for inductive reasoning (Muggleton and De Raedt, 1994), such as: *Inductive Logic Programming* and *Concept Learning*⁷. Thus, one can argue that the preference for simpler theories or terminologies should be maintained.

In (Sommer, 1995a), the author presents some intuitions on how simplifying a theory can cause it to be more understandable. It does so by appealing to an analogy between logic theories and free text. Textual sentences can be seen as a metaphor for logical predicates. Assuming this relationship, the paper continues to show that within linguistics and psychology (psycholinguistics) there is an inverse relationship between the complexity of the text and its understandability. The paper presents a

⁷Both particularly relevant to this work.

set of intuitions to define how understandable a theory is, this set can be summarized in:

1. A deeper theory is preferable to a shallow one.
 - The depth of a theory is the maximum number of inferences required to answer a goal query.
2. The longer the concept, the harder it is to understand it.
3. The more redundant a theory is, the less inclined one would be to accept it.

Sommer (1995a) presents another interesting argument as to why understandability should be considered in the machine learning setting. *Artificial intelligent* (AI) systems may be divided into (i)*symbolic*, such as: logical programs and ontologies, and (ii)*subsymbolic*, such as: neural networks and genetic algorithms, with regards to inspectability (Smolensky, 1987). In symbolical AI a model consists of symbols meant to be interpreted by humans. As a consequence, when a symbolic model is learned it can be inspected, interpreted and understood, and even lead to new insights about the domain. However, with subsymbolic AI a good solution is essentially a black box. Hence, when dealing with symbolic models understandability is a desirable trait.

Simplicity onto itself is a worthy goal of machine learning, however it should not be argued that choosing a simpler terminology over a more complex yield a better accuracy (Domingos, 1998). In this work, we have the main goal of learning terminologies that are more understandable (shorter) while still maintaining a comparable accuracy.

3 MULTIPLE CONCEPT LEARNING

In section 2.3 we presented the learning process for a single concept in Definition 2. Definition 5 presents the formal definition of the terminology learning task.

Definition 5 (Terminology Learning). *Let:*

- \mathcal{TL} be the terminology learning task, where $\mathcal{TL} = \{CL_{C_1}, \dots, CL_{C_n}\}$.
- CL_{C_i} be the concept learning task, $CL(C_i, \mathcal{E}_{C_i}, \mathcal{KB})$.
- \mathcal{KB} be the shared knowledge base for all concept learning tasks in \mathcal{TL} .
- \mathcal{T} be the terminology after the terminology learning task is completed.

For each $CL_{C_i} \in \mathcal{TL}$, find a concept definition C_i according to definition 2. Then, $\mathcal{T} = \mathcal{KB} \cup C_1 \cup \dots \cup C_n$.

When approaching the task of learning a terminology one could use two solution types: i) learning the concepts without including dependencies between concepts (independence assumption) or ii) learn the concepts regarding dependencies, henceforth called *Multiple Concept Learning* (MCL).

Suppose the following problem: we want to learn new concepts descriptions related to an existing terminology of the kinship domain (Fig. 2.2). The set of concepts we wish to learn is $\mathcal{TL} = \{CL(\text{GRANDPARENT}(\text{GP}), \mathcal{E}_{GP}, \mathcal{KB}), CL(\text{GRANDMOTHER}(\text{GM}), \mathcal{E}_{GM}, \mathcal{KB}), CL(\text{GRANDFATHER}(\text{GF}), \mathcal{E}_{GF}, \mathcal{KB})\}$. In order to learn each concept's description we have to define appropriate concept learning tasks for each concept in \mathcal{TL} . As previously defined, a concept learning

task is composed by a set of examples $\mathcal{E} = \langle \mathcal{E}_p, \mathcal{E}_n \rangle$ and the background knowledge \mathcal{KB} . Because all concepts in \mathcal{TL} belong to the same domain, the \mathcal{KB} can be shared. Suitable sets of examples need to be created using the individuals described in the \mathcal{KB} . After all this, we have defined a terminology learning task \mathcal{TL} .

After that we can learn definitions for each concept in \mathcal{TL} independently. However, because of our familiarity with the knowledge domain we know that dependencies between the concepts in \mathcal{TL} exists, for example, a proper definition for GRANDMOTHER can utilize GRANDPARENT.

Table 3.1: Example of the output of a terminology learning task with and without the independence assumption.

Concept	With Independence Assumption	Without
GP	$\exists PARENT.\exists PARENT.\top$	$\exists PARENT.\exists PARENT.\top$
GM	$FEMALE \sqcap \exists PARENT.\exists PARENT.\top$	$FEMALE \sqcap GP$
GF	$MALE \sqcap \exists PARENT.\exists PARENT.\top$	$MALE \sqcap GP$

Table 3.1 displays the results for the terminology learning task while uphold the independence assumption, and while regarding the dependencies among the concepts being learned. From this example we can see a suggestion that when the independence assumption is removed, the induced terminology is more compact and readable. This example inspired our hypothesis: “If dependencies among the concepts of the domain that need to be learned are found then clearer and compact terminologies are yielded while their quality is maintained.”

In this work, we present three alternatives for identifying concept dependencies aiming at finding more clear terminologies through their dependencies. They are:

- *Concept Dependency through Examples* (CDE): Devises a learning order suitable for finding dependencies. The order is extracted from a taxonomy built from the set of learning examples. The concept learned at iteration i can be included in the definition of concepts learned at iterations $> i$.
- *Concept Dependency through Assertions* (CDA): Allows the use of concepts that are not yet defined, in the form of assertions, during the learning of other

concepts, thus enabling the discovery of dependencies.

- *Concept Dependency through Terminology (CDT)*: Uses the redundancies found within a terminology to indicate when a dependency exists. A redundancy exists when a section within a definition can be replaced by another concept definition without any impact on the semantics. The terminology may already exist or be the output of a terminology learning task.

The methods CDE and CDA have a greater relationship to the concept learning process behaviour than CDT, specifically with its refinement operator. Candidate definitions are generated by the refinement operator using the DLs language constructors and \mathcal{KB} 's content. If, within a terminology learning task, a concept definition that was learned in a previous step is added to \mathcal{KB} it can be used while learning the next concepts. Next we have the definition for ensuring the shortest concept description within the MCL setting:

Definition 6 (Ensured Shortest Concept Description within MCL). *The shortest concept description for $CL_{C_i} \in \mathcal{TL}$, $\mathcal{TL} = \{CL_{C_1}, \dots, CL_{C_n}\}$, $i = 1, \dots, n$ is:*

$$CL(C_i, \mathcal{E}_i, \mathcal{KB} \cup_{i=1}^n S_{\mathcal{T}}/CL_{C_i}),$$

where:

- $S_{\mathcal{T}}$ is the set containing the solution for each $CL_{C_i} \in \mathcal{TL}$;
- $S_{\mathcal{T}}/CL_{C_i}$ is $S_{\mathcal{T}}$ minus the solution for CL_{C_i} .

When a concept is learned after all the other concepts in the terminology learning task, its learning process will have the largest amount of information compared to any of the other concepts in the terminology learning task, because it will have available the background knowledge and descriptions of all concepts learned in previous iterations. This ensures that any last concept will have the shortest description possible within its MCL setting, because if the best description for a concept contains a group of axioms that are equivalent to any other concept in the terminology learning task, the learning process can replace the group by the concept name, thus yielding

a shorter description. However, the best definition for a concept might not depend of all the other concepts in the terminology learning task. Thus, we can define the shortest concept description as:

Definition 7 (Shortest Concept Description within MCL). *The $best(CL_{C_i})$ for $CL_{C_i} \in \mathcal{TL}$, $\mathcal{TL} = \{CL_{C_1}, \dots, CL_{C_n}\}$, $i = 1, \dots, n$ is:*

$$CL(CL_{C_i}, \mathcal{E}_i, \mathcal{KB} \cup_{i=1}^n \{S_{\mathcal{T}} \cap best(CL_{C_i}).contains\}),$$

where:

- $S_{\mathcal{T}}$ is the set of solutions for \mathcal{TL} ;
- $best(X)$ is the shortest description for concept learning task X ;
- $X.contains$ is the set of concepts used in description X .

In the following sections we will present the methods for Multiple Concept Learning without the independence assumption in DL.

3.1 CONCEPT DEPENDENCY THROUGH EXAMPLES (CDE)

As seen in definition 7 the shortest solution for a concept learning task is yield when it is learned after all the concepts it depends on. In this section, we argue that finding out the subsumption relationship between concepts makes it is possible to yield an ordering of the concepts, which in return will support the learning of a rich – although simple and easily understandable – terminology. The question that arises is how to obtain a subsumption order from concepts that do not have definitions yet, i.e., before their definitions are learned. We tackle this problem by developing a procedure capable of finding out the relations among concepts *before* learning them, by taking advantage of their set of examples.

3.1.1 CONCEPTS DEPENDENCY

When using machine learning techniques to learn concepts, the examples are a mandatory component of the process, they mold the learned concept definition, distinguishing one concept from another. Because of the completeness and consistency

properties of the concept learning, the set of positive and negative examples provide strong evidence for the existence of dependencies and relationships among concepts. Thus, in this section we present a pre-learning phase MCL method based upon the set of examples for discovering concept dependency.

Let $CL(C_i, \{\mathcal{E}_{p_i}, \mathcal{E}_{n_i}\}, \mathcal{KB})$ and $CL(C_j, \{\mathcal{E}_{p_j}, \mathcal{E}_{n_j}\}, \mathcal{KB})$ be the concept learning tasks for concepts C_i and C_j respectively. After learning these concepts, their definitions will be part of the \mathcal{KB} 's *TBox*. Therefore, a comparative analysis of the individuals belonging to \mathcal{E}_{p_i} and \mathcal{E}_{p_j} points out how strongly related the corresponding concepts are and what might be the best order (\preceq) for learning them. Briefly, we argue that high similarity on the positive examples sets indicates high similarity between concept definitions. Example 5 illustrate this point.

Example 5. Let $CL(C_1, \mathcal{E}_1, \mathcal{KB})$, $\mathcal{E}_1 = \langle \mathcal{E}_{p_1}, \mathcal{E}_{n_1} \rangle$ and $CL(C_2, \mathcal{E}_2, \mathcal{KB})$, $\mathcal{E}_2 = \langle \mathcal{E}_{p_2}, \mathcal{E}_{n_2} \rangle$. Also, $\mathcal{E}_{p_1} = \{john, bob, edd\}$ and $\mathcal{E}_{p_2} = \{bob\}$ be the set of positive examples for concepts FATHER and GRANDFATHER, respectively. $\mathcal{E}_{p_2} \subseteq \mathcal{E}_{p_1}$, then the definition of concept FATHER will include more individuals than the definition of concept GRANDFATHER, thus being more general. Therefore, we argue that in the GRANDFATHER's definition the concept FATHER can be used, but not the other way around. Thus, if FATHER is learned and added to \mathcal{KB} before learning GRANDFATHER, then FATHER can be used to compose the definition of GRANDFATHER. A learning order is then established between the two concepts:

$$(\text{FATHER} \preceq \text{GRANDFATHER}).$$

The comparative analysis between two concepts (C_i and C_j) through their sets of positive examples comprises the following cases (Fig. 3.1 illustrates these cases):

1. Identical sets ($C_i \equiv C_j$): all elements belonging to one set also belong to the other set;
2. Disjoint sets ($C_i \cap C_j = \emptyset$): both sets have no elements in common;
3. Inner set ($C_i \subseteq C_j$): one set is a subset of the other;

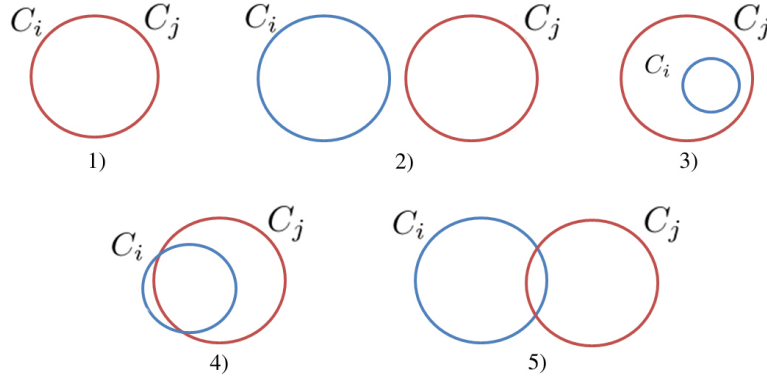


Figure 3.1: The relationship among concepts C_i and C_j through their positive examples sets, represented as Venn diagrams.

4. High intersection: the proportion of shared elements overcomes a threshold;
5. Low intersection: the proportion of shared elements does not overcome a threshold.

We claim that the higher is the intersection between sets of positive examples the greater is the relationship between the concepts. Thus, case 1 describes an upper limit, where the concepts are totally related, while case 2 indicates a lower limit, where the two concepts have no relationship. Furthermore, cases 1, 2 and 3, are the ideal cases because the underlying relationships between concepts are clear; on the other hand, the cases 4 and 5 need some mapping to one of the ideal cases, as “high” and “low” depends upon the observer. This is accomplished via a threshold value that will indicate how the concepts are related to each other. Therefore, the case 3 is a special case of 4, when the threshold is equal to 1; the case 2 is a special case of 5, when the threshold is equal to 0.

In this way, the relations among all concept definitions may be obtained from the comparative analysis of each pair of concepts that belong to the terminology learning task \mathcal{TL} . The resulting explicit relations among the concepts are translated to a subsumption tree (*a taxonomy*). For instance, consider the taxonomy depicted in Figure 3.2 for domain \mathcal{D} and set of concepts $N_C = \{C_1, C_2, C_3, C_4, C_5\}$.

The root node indicates the set of all individuals of the domain \mathcal{D} (\top concept). A concept in a branch on level i is more general than a concept on the same branch

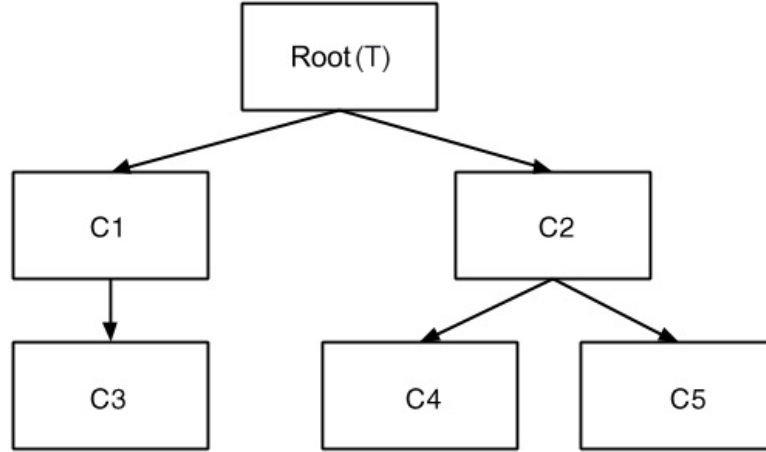


Figure 3.2: An example of a taxonomy depicting the relation among concepts C_1, C_2, C_3, C_4 and C_5 .

in level j , thus concept C_1 is more general than concept C_3 . Assuming that a more general concept can be used in the definition of a more specialized one, the latter should be learned first. Thus, the resulting taxonomy of the concepts can be used to determine the best ordering to learn the concept definitions.

3.1.2 LEARNING CONCEPT ORDERING

In Section 3.1.1, five possible results were detected after analyzing the relations between two concepts (C_i and C_j) through their sets of positive examples. From the first three cases, it is possible to directly acquire the relationship between the concepts. The two remaining cases requires a further analysis, aiming at deciding whether a subsumption relation is assumed or a total independence between C_i and C_j is a better choice. In this section, a procedure concerning the five possibilities is devised, which leads to a taxonomy of concepts.

Algorithm 1 presents the top-level procedure for building a taxonomy of concepts that is used to define an order for learning the concepts of a terminology.

The algorithm receives as input a terminology learning task, as outlined in Definition 5, and returns a taxonomy of its concepts. Given the ordering tree, a concept can only be defined if all its parents have already been defined. The root of the tree is a default concept which must be the father of all the concepts in \mathcal{TL} .

This algorithm starts by creating a tree with only the root. Next, each concept

Algorithm 1 Algorithm for learning a taxonomy of concepts

Require: a terminology learning task ($\mathcal{TL} = \langle CL_{C_1}, CL_{C_2}, \dots, CL_{C_n} \rangle$, where all $CL_{C_i} \equiv CL(C_i, \mathcal{E}_i, \mathcal{KB})$ is a concept learning task for concept C_i)

Ensure: a taxonomy of concepts \mathcal{T}

- 1: Starts \mathcal{T} with the concept \top in the root;
 - 2: Add each concept C_i considered in \mathcal{TL} as a child of the root;
 - 3: **for** each $CL_{C_i}, CL_{C_j} \in \mathcal{TL}$ **do**
 - 4: $\mathcal{T} \leftarrow$ call Algorithm 2 with $CL_{C_i}, CL_{C_j}, \mathcal{T}$
 - 5: **end for**
 - 6: **return** \mathcal{T}
-

(C_i) corresponding learning task (CL_{C_i}), where $CL_{C_i} \in \mathcal{TL}$, is included in the tree as child of the root. Then, Algorithm 2 is called for each pair of concepts C_i and C_j in order to find their relationship. After checking each possible dependency, the final taxonomy of concepts is returned.

In Algorithm 2 the relationship between the positive examples (\mathcal{E}_p) sets of the two concepts are analyzed in order to resolve in which of the five cases discussed in Section 3.1.1 it belongs. The algorithm begins by creating a variable that holds the amount of shared individuals between the example sets (line 1). The first case checked (line 2) is the one with two equivalent concepts, if that is the case the taxonomy is not modified, remaining the same as the previous iteration. In this way, both concepts are maintained unchanged in the resulting taxonomy, which makes possible to learn a proper definition for each one of them, even though they share the same set of positive examples. An alternative choice would be to keep only one of them in the taxonomy and later indicate in the terminology their equivalence. We chose the former because it is generally the case that the negative examples could be responsible for pointing out a different definition for each one of them.

Next, the algorithm verifies whether the concepts are disjoint (line 6). If this is the case, then there is no relationship between the concepts and the taxonomy is not changed. In case the set of positive examples associated to one concept is a subset of the other (line 9, 13), a relationship between them is included in the taxonomy. The *subsumee* concept is put as a child of the *subsumer* in the tree. Moreover, the

edge connecting the *subsumee* concept and the root is removed, as it is no longer necessary.

The two remaining decision are made according to the size of the intersection set between the two concepts. To decide whether the intersection is high or low, we employ a threshold parameter, that needs to be set before starting the process. The amount of intersection is computed by selecting the concept with less examples and dividing the number of shared individuals by its examples set size (line 24). In case this value is higher than the threshold, the procedure assumes that a relationship exists and the concept with more examples is included in the taxonomy as the *subsumer*, while the concept with less examples is included as its *subsumee* (line 25); again the relationship between root and the *subsumee* is removed. An important thing to notice is that only the root is removed as a parent of the *subsumee* concept; all the other parents it may have are maintained, such that the right order can be obtained.

3.1.3 LEARNING TERMINOLOGIES THROUGH CONCEPT ORDERING

Algorithm 3 presents the overall procedure for learning a terminology. It requires as input the terminology learning task \mathcal{TL} . As in our method it is necessary to find a taxonomy tree, so that a concept ordering is induced from such a tree, the first step of the algorithm is to call the procedure devised as Algorithm 1, which is going to return the tree comprising each concept addressed by the terminology problem.

Next, it is necessary to establish the order that the algorithm will follow to learn each concept description. This is done by traversing the tree in a breadth-first manner, and collecting all nodes at a level in order. For instance, considering the taxonomy in Figure 3.2, the concepts would be learned in the following order $\langle C_1, C_2, C_3, C_4, C_5 \rangle$. In this way, it is possible to guarantee that a concept is only handled after the descriptions for all its parents have been learned. This method allows for the discovery of unpredicted relationships because as ordering is devised between concepts in the same taxonomic level. Different treatment of same level

Algorithm 2 Algorithm for Ascertaining Dependencies among Concepts in a Terminology

Require: Concept learning tasks $CL(C_1, \{\mathcal{E}_{p_i}, \mathcal{E}_{n_i}\}, \mathcal{KB})$ and $CL(C_j, \{\mathcal{E}_{p_j}, \mathcal{E}_{n_j}\}, \mathcal{KB})$; a taxonomy \mathcal{T} .

Ensure: An updated taxonomy \mathcal{T}

```

1: sharedIndividuals  $\leftarrow 0$ 
2: if  $C_i \equiv C_j$  then
3:   return  $\mathcal{T}$ 
4: end if
5: sharedIndividuals  $\leftarrow |\mathcal{E}_{p_i} \cap \mathcal{E}_{p_j}|$ 
6: if sharedIndividuals = 0 then
7:   return  $\mathcal{T}$ 
8: end if
9: if  $\mathcal{E}_{p_i} \subseteq \mathcal{E}_{p_j}$  then
10:   include  $C_j$  as father of  $C_i$  in  $\mathcal{T}$ 
11:   remove ROOT from  $C_i$  parents set
12: end if
13: if  $\mathcal{E}_{p_j} \subseteq \mathcal{E}_{p_i}$  then
14:   include  $C_i$  as father of  $C_j$  in  $\mathcal{T}$ 
15:   remove ROOT from  $C_j$  parents set
16: end if
17: if  $|\mathcal{E}_{p_i}| \leq |\mathcal{E}_{p_j}|$  then
18:   smaller_concept  $\leftarrow C_i$ 
19:   larger_concept  $\leftarrow C_j$ 
20: else
21:   smaller_concept  $\leftarrow C_j$ 
22:   larger_concept  $\leftarrow C_i$ 
23: end if
24: if (sharedIndividuals / |smaller_concept|  $\geq$  threshold) then
25:   include larger_concept as father of smaller_concept in  $\mathcal{T}$ 
26:   remove ROOT from smaller_concept parents set
27: end if
28: return  $\mathcal{T}$ 

```

Algorithm 3 Top-Level Algorithm for Learning Terminologies

Require: A terminology learning task \mathcal{TL} .

Ensure: A Terminology \mathcal{TE}

- 1: find a Taxonomic Tree \mathcal{T} through Algorithm 1
 - 2: find an Ordered Sequence A_S of concept learning tasks \mathcal{TL} using \mathcal{T} , where concepts only come after their parents
 - 3: **for** each $C_k \in A_S$, in the established order **do**
 - 4: learn a description C_k from CL_{C_k} , using any algorithm that learns concepts in Description Logics
 - 5: include C_i in \mathcal{KB} for all $C_i \in A_S$ where $i > k$
 - 6: **end for**
 - 7: **return** \mathcal{TE}
-

concepts could be devised, however, this is not the main goal of the taxonomy.

Finally, each concept is learned gradually in order, through a loop that visits the concept learning task in the order defined in the second main step of the algorithm. To learn a description, the concept itself, its positive and negative examples and the current background knowledge are submitted to a description logic learning algorithm, such as DL-Learner (Lehmann and Hitzler, 2010), DL-FOIL (Fanizzi et al., 2008) or Yin-Yang (Iannone et al., 2007). Then, the description found is included in the TBox of each \mathcal{KB} of the following CL_{C_i} , so that it can be used in next iterations of the loop, as part of other descriptions. In this way, the learning algorithm can learn concept’s definitions according to the dependencies found in in Algorithm 2, in a rather ideal order discovered from the tree learned by the Algorithm 1. The algorithm ends by returning the terminologies learned at each step of the loop.

3.2 CONCEPT DEPENDENCY THROUGH ASSERTIONS (CDA)

As shown in definition 6 the shortest description for a single concept learning task within a terminology learning task is obtained when it is learned after all the other concepts, or when it is learned after all concepts it might depend on (definition 7). In summary it must find an answer for:

“What is the learning order that yields the shortest terminology?”

From definition 6, if it were possible to guarantee $S_{\mathcal{T}}/CL_{C_i}$ for any i we could find the best possible solution for the terminology \mathcal{T}^1 . On this section we provide a different view on the terminology learning problem, arguments and scenarios where it would be possible to obtain $S_{\mathcal{T}}/CL_{C_i}$ for any i . Furthermore, if that is possible, then the concept learning mechanism will be the sole responsible for the dependencies.

The question that arises is: “how can the definition for C_j be found before being learned?” In the remainder of this section we argue that under some conditions is possible to obtain a “definition” for C_j previous to its learning. Definition 8 underline the set of conditions under which this is possible.

Definition 8 (CDA’s Restrictions). *The following are restrictions for the proper work of the method CDA:*

1. *The background knowledge is a finite model.*
2. *For every concept C in terminology learning task $\mathcal{T}L$ and every individual I relevant to the concept C , $I \in \mathcal{E}_{P_C}$ or $I \in \mathcal{E}_{N_C}$.*

The domain owner has to investigate if it is possible or desirable to uphold restriction 2. Naturally upholding this restriction may be reasonable because the amount of information on \mathcal{E} tends to yield better results.²

When CDA’s restrictions are uphold, because of the idea presented in definition 4, its possible to use the sets of examples \mathcal{E}_i of each concept learning task within a terminology learning task $\mathcal{T}L = CL_{C_1}, \dots, CL_{C_n}$, as a surrogate for the definition that will be found later with no semantic lost. There is no difference with regards to the result obtained from the reasoning services for a query $C(a)$, if it is an assertion (ABox) or this follows from the terminology (TBox.)

This has an added benefit that each concept learning task can be executed independently, allowing for parallel learning of each concept.

Example 6 shows the output of the terminology learning task for the set of concepts $\{\text{GRANDPARENT}(\text{GP}), \text{GRANDMOTHER}(\text{GM}), \text{GRANDFATHER}(\text{GF})\}$.

¹Contingent upon SCL returning the best solution.

²This is a general principle on Machine Learning: The amount of relevant information positively affects the quality of learned models.

With CDA's local goal, it is possible to find the shortest description for each concept (notice GP). This spurs the rise of a problem as depending on the set of concepts, cycles may be formed³. This goes against one of the general assumption we need to uphold - concept definitions are acyclic (section 2.1). We propose two approaches to deal with cycles: (i) restrict the set of examples added to \mathcal{KB} ; (ii) remove the cycles on a post procedure.

Example 6. Let \mathcal{KB} be as presented in Figure 2.2, $\mathcal{TL} = \{CL_{GP}, CL_{GM}, CL_{GF}\}$. Executing CDA we have the resulting terminology \mathcal{T} :

- $GP \equiv GM \sqcup GF$
- $GF \equiv GP \sqcap male$
- $GM \equiv GP \sqcap female$

(i) If a concept C_j of the concepts in \mathcal{TL}/CL_{C_i} , $i \neq j$, already has a definition and it uses C_i do not include C_i or C_j in \mathcal{KB} . This prevents that any new definition creates a cycle. As a consequence, an order for the learning process may be necessary. In this case the best acyclic solution is not guaranteed.

(ii) After the end of the learning phase, identify the concepts that incurred in cycles and relearn them, avoiding the current or a recurring cycle. Choose the definitions that yield smaller definitions.

The second method have a better chance to return the optimal acyclic solution, but may relearn several concepts, thus the first method is likely to be more efficient. In both methods the best acyclic solutions is not guaranteed.

3.2.1 CDA WITH CYCLE REMOVAL

As stressed earlier on this chapter the normal CDA method has a great probability of inducing terminologies containing cycles. As one of the possible approaches to deal with cycles is to remove them after the terminology is obtained, the rest of this section will present such method.

³The definition for GP makes a cycle.

The proposed method will only deal with cycles with depth⁴ of one, Example 7 displays a terminology with a cycle of depth one. However, the following algorithms can be modified to work with deeper cycles if a cycle checking is defined and alternative definitions⁵ for all concepts in the cycle are found. We left the implementation of deeper cycle removal for a future work.

Example 7. *The terminology containing the concepts: $A \equiv B \sqcap C \sqcap D$ and $B \equiv F \sqcap D \sqcup A$, has a cycle with depth of one, because the concept A appears in the definition of B while it uses B within its definition, needing only one inferential step before incurring in a cycle.*

The Algorithm 4 is the entry point for the learning process. It runs the CDA for the terminology learning task and call the Algorithm 5 to remove the cycles of the learned terminology.

Algorithm 4 CDA with Cycle Removal Main algorithm

Require: A terminology learning task \mathcal{TL} .

Ensure: A Terminology \mathcal{TE}

- 1: **for** each $CL_{C_i} \in \mathcal{TL}$ **do**
 - 2: Add \mathcal{TL}/CL_{C_i} example sets into \mathcal{KB}'
 - 3: Change CL_{C_i} 's \mathcal{KB} to \mathcal{KB}'
 - 4: Learn a description C_i for CL_{C_i}
 - 5: **end for**
 - 6: $\mathcal{TE} \leftarrow$ call Algorithm 5(\mathcal{TL})
 - 7: **return** \mathcal{TE}
-

The Algorithm 5 is used to remove the cycles of a set of concept learning tasks. It starts by defining an empty map of blocked concepts. A concept C_j is a blocked concept for the learning of a concept C_i , if in a previous iteration there was a cycle between C_i and C_j and C_i 's definition was altered. Furthermore, it creates a set of concepts that are in need of cycle verification, beginning with all the concept learning tasks.

While there are concepts to check for cycles, it chooses two concepts within this set to verify if there is a cycle involving them. If a cycle exists between two

⁴Depth is the number of inferential steps taken until a cycle is found.

⁵The alternative definitions should be constructed in a way to prevent the same recurring cycle.

concepts, it creates a new \mathcal{KB} using the existing \mathcal{KB} together with the set of concepts not blocked (lines 13, 14). All the dependents of a blocked concept are themselves blocked concepts. Finally, alternative definitions are learned for both concepts using their “new” \mathcal{KB} s.

Once the alternative definitions are acquired, one must choose which of the two concepts will receive the alternative definition (line 17). The choice is made in favor of the alternative definition with the smallest impact on the terminology, i.e., the one with least difference in length with regards to the original definition. Lastly, the concept learning task whose definition was altered has to be verified, because new cycles may have been introduced, and the other concept learning task is added to alter concept’s blocked set.

Algorithm 5 Remove cycles from learning tasks algorithm

Require: A set of learning task \mathcal{TL} with definitions.

Ensure: A Terminology \mathcal{TE}

```

1: mapBlockedConcepts  $\leftarrow \emptyset$  {Contains the set of concepts blocked from the learn-
   ing of each concept}
2: conceptsToVerify  $\leftarrow \mathcal{TL}$ 
3: while conceptsToVerify  $\neq \emptyset$  do
4:    $C_i \leftarrow \text{conceptsToVerify.pop}$ 
5:    $C_j \leftarrow \text{null}$ ;
6:   for each  $A_p \in \text{conceptsToVerify}$  do
7:     if There is a cycle between  $C_i$  and  $C_p$  then
8:        $C_j \leftarrow C_p$ 
9:       break from the for loop
10:    end if
11:  end for
12:  if  $C_j \neq \text{null}$  then
13:     $\mathcal{KB}_{C_i} \leftarrow \mathcal{TL} / \{C_j \cup \text{Dependents of } C_j \cup \text{mapBlockedConcepts of } C_i\}$ 
14:     $\mathcal{KB}_{C_j} \leftarrow \mathcal{TL} / \{C_i \cup \text{Dependents of } C_i \cup \text{mapBlockedConcepts of } C_j\}$ 
15:    Learn a description  $D_i$  for  $C_i$ , using any algorithm that learns concepts
    in DL with  $\mathcal{KB}_{C_i}$ 
16:    Learn a description  $D_j$  for  $C_j$ , using any algorithm that learns concepts
    in DL with  $\mathcal{KB}_{C_j}$ 
17:     $C_b \leftarrow C_i$  or  $C_j$  by the best description between  $D_i$  and  $D_j$ 
18:    add  $C_b$  to conceptsToVerify
19:    add the other concept to the blocked concepts of  $C_b$ 
20:  end if
21: end while
22: return  $\mathcal{T}$ 

```

3.3 CONCEPT DEPENDENCY THROUGH TERMINOLOGY (CDT)

The technique to compact existing definitions proposed in this section is motivated by the fact that if part of the definition has a semantically equivalent but syntactically smaller counterpart, then a substitution could take place generating a smaller though equivalent definition. Henceforth we call this process *syntactic compression*. In the following section, we present our method for *syntactic compression*.

In (Melo et al., 2014) this approach received the name *R2D2* for “**R**edundancy **R**emoval on **D**Ls **D**escriptions”. In the remainder of this work, we will interchangeably refer to this method as R2D2 or CDT.

3.3.1 SYNTACTIC COMPRESSION USING TREE REPRESENTATION

In order to achieve a syntactic compression it is necessary to find viable substitutions, i.e., parts of a concept definition that encompass another concept. Example 8 illustrates a possible syntactic compression.

Example 8. *Let A, B, C, D and E be concepts in a DL such that concept $A \equiv C \sqcap D \sqcup E$ and concept $B \equiv D \sqcup E$. The section $D \sqcup E$ within A encompasses concept B . Therefore, concept A can be rewritten as $A \equiv C \sqcap B$.*

At a first glance, the syntactical compression may be done performing a simple matching of the two logical definitions. However, this approach is very likely to not produce all possible substitutions, since most of DL’s constructors are commutable, as shown in Example 9.

Example 9. *The logical definition $B \sqcap C \sqcap D$ is equivalent with any conjunction of permutations of the concepts $\{B, C, D\}$, such as: (i) $B \sqcap D \sqcap C$, (ii) $D \sqcap B \sqcap C$, ...*

In order to overcome this limitation, while still performing a syntactic compression, we propose the use of a n-tree representation of the concepts definitions. In this tree: (i) internal nodes represent a constructor, (ii) leaves represent concepts,

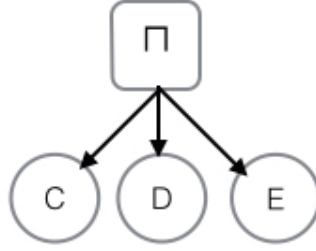


Figure 3.3: Example 10's syntactic tree representation.

and (iii) all children of a constructor node are commutable. Allowing the commutation of the constructor's node children is essential, since identical definitions, unless for the order of literals, should have the same associated tree. This is illustrated in Example 10.

Example 10. *Let A, B, C, D, E concepts in a terminology, such that concept $A \equiv C \sqcap D \sqcap E$ and $B \equiv E \sqcap C \sqcap D$. Fig. 3.3 shows the representation for both concepts.:*

Fig. 3.4 shows all the correlations between \mathcal{ALC} 's constructors and their tree representation. We stress that the proposed method is language independent as long as it is possible to separate the constructors of the DL language between unary and binary (commutable n-ary) constructors.

3.3.2 REDUNDANCY REMOVAL ON DLS DESCRIPTIONS (R2D2)

Algorithm 6 presents our procedure to execute the syntactic compression of a terminology.

The algorithm receives as input a set of concepts descriptions (terminology), and a set of available constructors, divided into unary and n-ary, and returns a set of compressed concept descriptions.

It starts by sorting the set of concepts in ascending order of length (Definition 3). This is an important step, because a concept can only have a substitution involving a smaller concept.

Next, for each concept in the terminology it finds its corresponding tree form (line 4). This step is better visualized through Algorithms 7 and 8, that we discuss later. Once it has the tree representation of all concepts, it can proceed to find

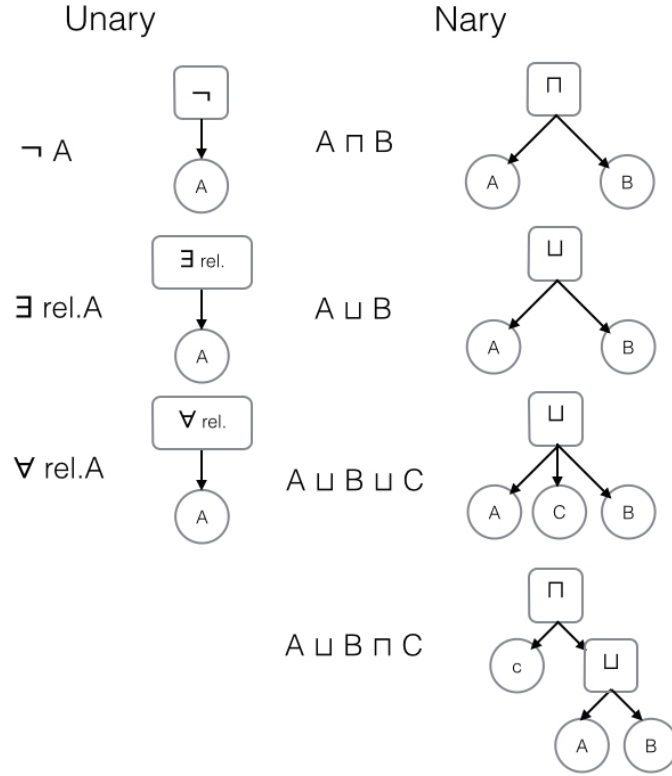


Figure 3.4: The syntactical tree representation of \mathcal{ALC} 's constructors.

suitable substitutions. It does so by exhausting all the pairs of concepts with a smaller concept and a larger one (line 6), and calling Algorithm 9 (line 7) to find a proper substitution. After all the substitutions are made, it changes the modified original concept definitions by translating the tree representation back to its logical form (line 10). The translation method is done via a pre-order traversal in the tree.

SYNTACTIC TREE CONSTRUCTION

Algorithms 7 and 8 are used to parse the logical syntax into the tree representation. In case all the n-ary constructors have the same precedence, as it is the case of \mathcal{ALC} language, we still need a way to distinguish them in the tree. We do so by creating a hierarchy in the tree with them. Thus, the line 22 of algorithm 7 creates a subtree as soon as it identifies a constructor different from the previous one. In case the DL language defines a different precedence rule than \mathcal{ALC} , the algorithm must be changed to attend such a rule.

In the syntactic representation, a block is a part of the definition enclosed within parenthesis, a block may contain other blocks. The upper and lower bound are,

Algorithm 6 Syntactical Compression Main Algorithm

Require: a set of concept definitions $C_d = \{C_1, \dots, C_n\}$ and the set of valid constructors in the DL

Ensure: a set of compressed concepts definitions $C'_d = \{C'_1, \dots, C'_n\}$

```

1: sort  $C_d$  by concept definition length;
2:  $\mathcal{T}_c \leftarrow \{\}$ 
3: for each  $C_i \in C_d$  do
4:    $\mathcal{T}_c.add$  Algorithm 7( $C_i$ , 0,  $C_i$  length, valid unary constructors, valid nary constructors);
5: end for
6: for each pair  $\mathcal{T}_{ci}$  and  $\mathcal{T}_{cj}$  in  $\mathcal{T}_c$ , where  $i < j$  do
7:   Algorithm 9( $\mathcal{T}_{ci}$ ,  $\mathcal{T}_{cj}$ );
8: end for
9: for each  $\mathcal{T}_{ci} \in \mathcal{T}_c$  do
10:   $C_i \leftarrow \text{TreeToDefinition}(\mathcal{T}_{ci})$ ;
11: end for
12: return  $C_d$ 

```

respectively the begin and end of a concept or block.

FINDING PROPER SUBSTITUTIONS

Algorithm 9 is used to perform substitutions between two trees. It receives two trees: a larger tree and a smaller tree. To perform a substitution, it must find a node within the larger tree that is the root of the smaller tree (line 4). In this representation, a larger tree contains a subtree equivalent to a smaller tree when: i) all the internal nodes in the smaller tree have an equivalent node in the larger tree subtree (also with equivalent arcs), and ii) the subtree root of the larger tree contains all the nodes below the smaller tree root. Example 11 shows why the second restriction does not state that the larger tree subtree's root should be equal to the smaller tree's root. The problem of finding an equivalent tree is also known in the literature as *tree isomorphism* (Zemlyachenko et al., 1985).

Example 11. Let $F \equiv A \sqcup B \sqcap C$ and $E \equiv A \sqcup B$. Executing the substitution on the tree representation of F and E we have:

Algorithm 7 Logical Description to Syntactical Tree

Require: a concept description C ; a lower bound; an upper bound; a set of unary constructors $S_u = U_C1, \dots, U_Cn$ and a set of nary constructors $S_n = N_C1, \dots, N_Cn$

Ensure: A syntactical Tree $root$

```

1: create an empty  $root$ ;
2: create the auxiliary variable  $firstConcept$ ;
3:  $index \leftarrow lowerBound$ ;
4: while  $index \leq upperBound$  do
5:    $currentConstruct \leftarrow C[index]$ ;
6:   if  $currentConstruct$  is a block then
7:      $aux \leftarrow \text{Algorithm 7}(C, index, \text{end block index}, S_u, S_n)$ ;
8:     if  $root$  is empty then
9:        $root \leftarrow result$ ;
10:    else
11:      merge  $root$  with  $result$ ;
12:    end if
13:    increment index;
14:    continue to next loop iteration;
15:  end if
16:  if  $currentConstruct \in S_n$  then
17:    if  $root$  is empty then
18:       $root \leftarrow currentConstruct$ ;
19:      if  $firstConcept$  is not empty then
20:        add  $firstConcept$  as a child of  $currentConstruct$ ;
21:      end if
22:      if  $root \neq currentConstruct$  then
23:        add  $root$  as a child of  $currentConstruct$ ;
24:         $root \leftarrow currentConstruct$ ;
25:      end if
26:    end if
27:    increment index;
28:    continue to next loop iteration;
29:  end if
30:  if  $currentConstruct \in S_u$  then
31:     $currentConstruct \leftarrow \text{Algorithm 8}$ ;
32:     $index \leftarrow \text{end index returned in line 31}$ ;
33:  end if
34:  if  $root$  is empty then
35:     $firstConcept \leftarrow currentConstruct$ ;
36:  else
37:    add  $currentConstruct$  as a child of  $root$ ;
38:  end if
39: end while
40: if  $root$  is empty AND  $firstConcept$  is not empty then
41:    $root \leftarrow firstConcept$ ;
42: end if
43: return  $root$ 

```

Algorithm 8 Recursive Method for Unary Constructors

Require: a concept description C ; a lower bound; a set of unary constructors $S_u = U_C1, \dots, U_Cn$ and a set of nary constructors $S_n = N_C1, \dots, N_Cn$
Ensure: A syntactical Tree *node* and the ending index

```

1:  $index \leftarrow lowerbound$ ;
2:  $currentConstruct \leftarrow C[index]$ ;
3: if  $currentConstruct \in S_u$  then
4:   if  $currentConstruct$  is a unary quantifiers then
5:      $currentConstruct \leftarrow$  all items from index to relation statement;
6:   end if
7:    $currentConstruct.descendent \leftarrow$  Algorithm 8;
8:    $index \leftarrow$  Algorithm 8 index;
9: else
10:  if  $currentConstruct$  is a block then
11:     $currentConstruct \leftarrow$  Algorithm 7( $C$ , index, end block index,  $S_u$ ,  $S_n$ );
12:     $index \leftarrow$  end block's index;
13:  end if
14: end if
15: return  $currentConstruct$  and  $index$ 

```

Algorithm 9 Syntactical Compression's Substitution

Require: larger tree \mathcal{T}_l ; smaller tree \mathcal{T}_s

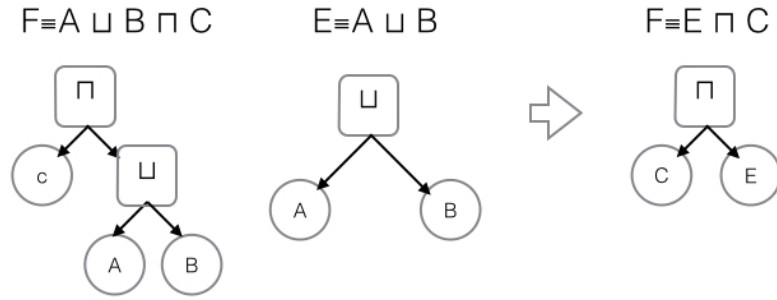
```

1:  $nodesToVerify \leftarrow \{\mathcal{T}_l.root\}$ ;
2: while  $nodesToVerify$  is not empty do
3:    $rootLarger \leftarrow nodesToVerify.pop$ ;
4:   if  $rootLarger \equiv \mathcal{T}_s.root$  then
5:      $rootLarger \leftarrow \mathcal{T}_s$  concept;
6:   end if
7:   add  $rootLarger$  in  $nodesToVerify$ ;
8: end while

```

Table 3.2: Comparison matrix for solutions: CDE, CDA and CDT.

	TBox Dependent	Abox Dependent	Language Independent	Order	Preferred Constructor	Processing	Generates Cycles
CDE	No	Yes	Yes	No	\sqcap	Sequential	No
CDA	No	Yes	Yes	No	None	Parallel	Yes
CDA1	No	Yes	Yes	Yes	None	Sequential	No
CDA2	No	Yes	Yes	No	None	Sequential	No
CDT	Yes	No	Yes	No	None	Sequential	No



3.4 SUMMARY OF METHODS

In this section we describe some of the aspects of each of the proposed methods for Multiple Concept Learning. Table 3.2 list the properties compared for each of the methods. In this table the CDA method is divided into tree configurations:

- **CDA**: Regular CDA solution;
- **CDA1**: CDA with cycle avoidance;
- **CDA2**: CDA with cycle removal;

The first and second columns of Table 3.2, shows which methods are TBox and ABox dependent, respectively. CDT is the only method that requires a pre-existing terminology. This terminology can be defined manually or be the product of a terminology learning task. On the same token, CDT is independent of ABox, while all the other solutions are dependent on an existing ABox. This is the case because all the solutions, excepting CDT, are tightly related to the terminology learning task, for this reason CDT can be used outside the context of a terminology learning task.

The reliance of CDE and CDA solutions on the set of examples to induce terminologies with dependencies leads to

Because of CDE and CDA reliance on the set of examples and the shared individuals within these sets to induce terminologies with dependencies, both methods, and their variants, are improved with a premise related to the completeness of the examples. Usually, there are no rules related to how one chooses the set of examples for the learning task, it only needs to contain relevant individuals for the concept being learning, there are no indications of how significant this sample of the domain should be.

For CDE and CDA, even when assuming the background knowledge (\mathcal{KB}) is shared by the concept learning tasks in a terminology learning task, there is no guarantee that the same set of individuals will be used as examples for all concept learning tasks. If this is the case, CDE and CDA methods would fail at finding relationships because they use a comparative analysis of the shared individuals to inform the dependencies found.

Therefore, to improve the quality of the dependencies found, we may add the following conditions: i) all concept learning tasks in a terminology learning task must relate to the same knowledge base; ii) all concept learning task examples must relate to the same set of individuals. In this case, all the individuals belonging to a subset of \mathcal{KB} should be classified as either a positive or negative example⁶. This burden may be too big for the domain experts.

All the solutions are not dependent on a particular DL language (Column 3). This means that all the solutions can be used with any DL language available without any additional configuration. However, this does not mean that the solutions will have the same performance in all the possible languages, in these cases the heuristics could be tweaked to better suit the chosen language. In this master dissertation we used DL-Learner as the learning component of our solutions. DL-Learner's default language is \mathcal{ALCN} .

⁶See Appendix A for a further reading about the relationship of OWA and CWA to inductive and inferential reasoning.

The fourth column, labeled “Order”, indicates if the terminologies found using the solution are affected by the order in which the concept learning tasks are inputted. CDA1 is the only solution directly affected by the concept learning task ordering. The order affects CDA1 because it is used to avoid the formation of cycles. One important thing to notice, it that CDE is not affect by the inputted order, although its main goal is to establish a learning order. CDE is not affected because it creates its orders based on the concept learning tasks set of examples.

The fifth column, displays the preferred constructor of each solution. CDE is the only solution with a preferred constructor. As discussed in its section, the heuristic use to construct the taxonomy of concepts and the way it is traversed to extract the learning order, implies a predilection for expressing the dependencies among concept with conjunctions (\sqcap). This happens because the order assumes that a concept with a smaller set of examples can be properly defined using the larger in conjunction with other description (C).

The sixth column, labeled “Processing”, displays the manner that the concept learning tasks within a terminology learning task can be executed, or in CDTs case how the concept descriptions are managed. The concept learning tasks can be processed either sequentially or in parallel. CDE, CDA1, CDA2 and CDT are processed sequentially, while CDA can be executed in parallel.

The sixth column is directly related to the seventh column. The seventh column, displays which of the approaches can produce terminology containing cycles. This is particularly important because one of the most commonly upheld assumptions in DL’s is that terminologies are acyclic, however this is not always the case. All the solutions, with exception of CDA, do not generate cycles.

CDA’s goal of finding the shortest description and the used of assertions as surrogates for definitions, it can yield the shortest terminologies, although this leads to cycles. But because of the prevalence of the acyclic assumption we developed two alternative version of CDA: CDA1 - avoiding the cycles and CDA2 - removing the cycles. The second solution (CDA2) has a better chance to return the optimal

acyclic solution, but may relearn several concepts, thus the first method (CDA1) is likely to be more efficient. In both methods the best acyclic solutions is not guaranteed.

4 EXPERIMENTS

To validate the hypothesis and the proposed solutions we used the experimental method. This chapter presents the experimental methodology and it is divided in three sections. The first one describes the set of datasets used throughout the experiments. The second section describes the experiments pertaining each proposed method (CDE, CDA and CDT). The third and last section describes the experiments to compare all the proposed methods and single concept learning.

4.1 DATASETS

The following are the problems used in the experiments.

- **Kinship**: defines family relations through a very simple terminology, containing only three roles (*sibling*, *married* and *parent*) and two atomic concepts (*male* and *female*). The set of concepts used for learning was $\{Grand\ Parent\ (GP),\ Grand\ Father\ (GF),\ Grand\ Mother\ (GM)\}$, obeying their regular semantic. Each concept in this set is interdependent of the others, i.e., one could generate a proper concept definition using a combination of the remaining ones, e.g., $GM \equiv GP\ AND\ female$, or $GM \equiv GP\ AND\ NOT\ GF$.
- **Moral Reasoner**(Wogulis, 1994): this dataset describes moral statements such as “Someone is guilty of an action if it is blameworthy or he/she takes the blame for someone else”. It has a large terminology composed of 25 primitive concepts and 20 non-primitive concepts. Additionally, the ABox has assertions for 202 individuals. However, not all the assertions about non-primitive

concepts are represented, in these cases it is necessary to make inferences to discover them. Since this is a more elaborate dataset than the Kinship, it can lead us to interesting conclusions about the proposed methods. Towards that, two experiments were done with this dataset. In the first one (Exp1), the concepts chosen to be learned were $\{guilty, blameworthy, responsible, notaccident\}$, and in the second one (Exp2) $\{guilty, blameworthy, responsible, notaccident, weak_intend, intend_c\}$, increasing the learning process complexity with two more concepts. The concepts for each set of problems were arbitrarily chosen because of their interdependencies, however other sets of concepts could have been used.

- **OAEI campaign:** CDT’s method can deal with terminologies that do not have individuals (ABox) because it works only with concept’s descriptions (TBox). Because of this we could devise a different more broader set of problems to validate CDT’s approach. We devised a validation experiment using a larger set of problems, containing a number of datasets of OAEI¹’s 2013 campaign of ontology matching and all datasets packaged as examples on DLELearner system². In total, there were 46 datasets with a wide range of domains, for example the kinship, moral, biomedical, and sizes, ranging from 0 to 10480 complex concepts.

4.2 EXPERIMENTS FOR EACH INDIVIDUAL METHOD

4.2.1 CDE: FINDING THE BEST THRESHOLD VALUE

CDE is a method that creates an order over the concepts that a multiple concepts learning algorithm should follow. It uses a threshold parameter that defines a lower limit for the proportion of intersection between two concepts, after which the concepts are considered dependent by the method. In (Melo et al., 2013b) the threshold value was arbitrarily set to 80%. Here, we would like to empirically decide

¹<http://oaei.ontologymatching.org/>

²<http://dl-learner.org/Projects/DLELearner>

which is the best value for the threshold parameter.

The issue that arises here is what “best” means in this context. The CDE method analyses the concept’s set of positive examples two by two and check whether the proportion of shared examples over the amount of examples within each set is higher than the threshold. This information is then used to build the taxonomy, which in turn is used to define the learning order. Thus, the best threshold value would be the one in which the taxonomy found by CDE is identical to a taxonomy built from the relationships found on the learned terminology, i.e., the relationships predicted by the induced taxonomy should also appear in the learned terminology.

Thus, to analyse the behaviour of CDE approach according to the threshold parameter, we set it to 20%, 40%, 60%, 80% and 90% and computed the matching relationships using the *moral reasoner dataset*. Table 4.1 presents the average predictive results we found, the second column presents the threshold’s value, the values were aggregated if more than one result were the same, where the third column shows the number of predictions returned by the induced taxonomy, the fourth column shows the subset size of relationships that were indeed considered in the learned terminology and the fifth column shows the number of found dependencies that matched those presented in the target description, we called this metric *Hits*. The results indicate that indeed the arbitrarily set threshold is a good value, followed closely by 90%. As it should be expected, requiring only a low intersection between two sets of examples yields a high number of predictions that are not actually established during the learning phase. An interesting phenomenon occurred in the problem “exp2” with thresholds of 80% and 90%, in these scenarios relationships different from those of the target concepts were found, this indicates that the terminology learning task chosen has a wide variety of possible relationships with valid descriptions.

4.2.2 CDA

CDA adds the learning examples to the background knowledge in order to induce the shortest solution for a single concept learning task (Definition 7). We devised

Table 4.1: CDE: Best Threshold Experiment.

Exp.	Threshold	# Pred.	# Relations Found	# Hits	Hits over Pred.
exp1	(0.8, 0.6, 0.4, 0.2, 0.1)	6	4	4	0.67
	0.9	3	2	2	0.67
exp2	(0.4, 0.2, 0.1)	15	4	4	0.27
	0.6	13	4	4	0.31
	0.8	9	4	3	0.33
	0.9	4	5	2	0.5

Table 4.2: CDA’s validation experiment results.

Experiment	Concept	Definition	Length
CL	GP	EXISTS parent.EXISTS parent.TOP.	5
	GF	(male AND EXISTS parent.EXISTS parent.TOP).	7
	GM	(female AND EXISTS parent.EXISTS parent.TOP).	7
CDA	GP	(grandfather OR grandmother).	3
	GF	(grandparent AND male).	3
	GM	(grandparent AND female).	3

an experiment using the kinship toy example in order to validate this claim. In this experiment we will not uphold the assumption that the terminology must be acyclic, we did this because we would like to know if CDA’s surrogates are indeed correct and can yield the shortest description for all the concepts in a terminology learning task. Table 4.2 shows the result for this experiment contrasting with the result achieved with the CL method.

CDA achieves a terminology with the length 9, while CL found a terminology with the length of 19. Furthermore, CDA found the shortest possible solution for all three concepts in the terminology learning task.

4.2.3 CDT

Different from the CDE and CDA, CDT (R2D2) can be used outside the terminology learning problem, because it is a method for theory restructuring.

In order to evaluate we used the R2D2 validation dataset described earlier. Table 4.3 presents the results obtained from R2D2 for each one of the 46 datasets. Most of the datasets have terminologies with only atomic concepts and roles (ABox), in these cases the method does not propose any replacements on the original terminology since there is nothing to compress. In most of the other cases the method had no

Table 4.3: CDT: Results of the validation experiment.

Dataset	#Concepts	Original Size	Post Size	Exec Time in secs.
DL Arch	5	18	18	.018273
DL Family-Father	1	2	2	.001455
DL Family-Uncle	1	3	3	.004273
DL Forte-Family	1	3	3	.001455
DL MoralReasoner	20	133	133	.032727
DL MoralReasoner(43)	19	130	130	.034091
DL MoralReasoner(43 Complex)	17	112	112	.025364
OAEI conf_cmt	1	5	5	.001364
OAEI conf_Cocus	5	19	17	.005727
OAEI conf_Conference	13	49	49	.024364
OAEI conf_confious	8	24	24	.011273
OAEI conf_edas	7	42	42	.011091
OAEI conf_PCS	4	12	12	0
OAEI conf_sigkdd	7	21	21	.01
OAEI NCL_smallOverlapping_fma	1964	17046	17046	55.59373
OAEI SNOMED_smallOverlapping_fma	2882	35552	35552	86.63409
OAEI NCL_smallOverlapping_snomed	6851	74191	74183	684.26991
OAEI NCL_while_ontology	10280	151316	151308	1997.30955
Rest of datasets (#28)	0	0	0	0

impact on the size of the terminology. With further analysis this happened because the terminologies were already syntactically compressed, then the terminology after the method has the same length as earlier. More than anything, this might be a testament of the quality of the terminologies.

The method achieved *syntactic compression* on only three of the forty-six terminologies:

- conf_Cocus;
- NCL_smallOverlapping_fma.owl;
- NCL_while_ontology.owl.

Next we will analyse each substitution.

conf_Cocus: the original terminology was composed of five complex concepts (Administrator, Document, Event, Event_Setup and User), with “Document” and “Event” having the same definition: “ $\exists created_by.Person$ ”. The method arbitrarily

substituted one of the definitions by the other concept, as an example resulting in: *Event* \equiv *Document*. In this particular case, it might be argued that the real meaning is lost when this substitution is performed, but from a pure logical point of view the semantic is maintained.

NCLsmall_overlapping_fma.owl and *NCLwhole_ontology.owl*: both terminologies pertain to the same domain of biomedicine, sharing much of the concepts and definitions. Looking closely we can see that the terminology *NCLwhole_ontology.owl* contains *NCLsmall_overlapping_fma.owl*. Both had the same two substitutions: the concept “Complement_Component-4” was substituted by its definition on concepts “Complement_Component-3” and “Complement_Component-5”. Both concepts where the substitution occurred had a structure of many conjunctions of existential restrictions. These particular replacements are difficult to visualize because of the size of the concepts (41 and 57 respectively). This might suggest a direct relationship between a terminology size and complexity and how difficult it is to find all simplifications. For humans there seems to be a limit over which a terminology or concept is too complex to one entertain all possible substitutions. These experiments suggests that the use of R2D2 has the potential to yield terminologies as simple as syntactically possible, provided that the computational cost is not too high.

R2D2 COMPUTATIONAL BEHAVIOUR

In this section we try to establish the relationship between the execution time of the R2D2 and the amount of concepts and size of a terminology.

To evaluate this we ran the evaluation experiment ten times and calculated the average execution time for each terminology. Fig. 4.1 shows the relationship between the number of concepts/size of terminology and the execution time.

It is important to stress that, although it seems that there would be an exponential increase in the execution time as terminologies gets larger than the biggest tested, is highly unlikely that terminologies would have much more than 10280 concepts and 151316 in size. Having the 10280/151316 as a soft limit for the complexity, the 20 to 30 minutes of execution time seems reasonable.

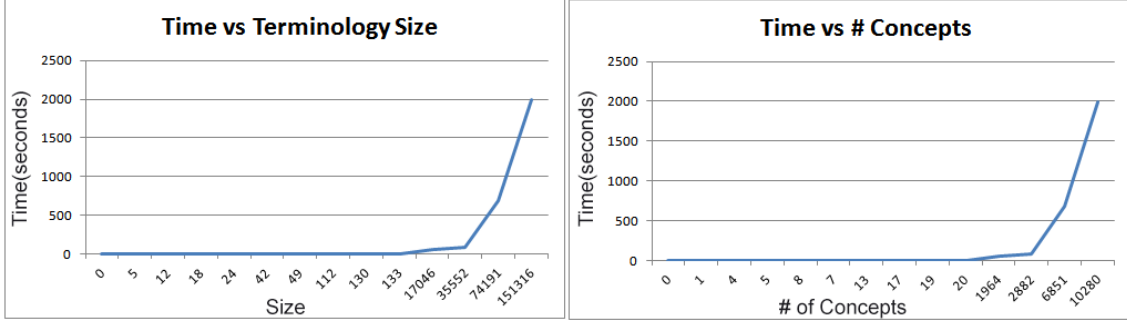


Figure 4.1: R2D2’s Execution time vs Number of concepts and Terminology size.

4.3 EXPERIMENTS COMPARING METHODS

In this section, we describe experiments conducted towards comparing CDE, CDA and CDT. The experimental design consisted of the following steps:

1. select a problem that has an associated terminology with interdependent concepts;
2. select a set of concepts within the terminology to compose the concept learning tasks (CL_{Ci});
3. define the knowledge base (\mathcal{KB}) and the sets of examples (\mathcal{E}_{p_i} , \mathcal{E}_{n_i}) for all CL_{Ci} . The latter is performed either directly from the original examples or by performing inference along the terminology and the knowledge base. While the \mathcal{KB} is the same in all CL_{Ci} , \mathcal{E}_{p_i} and \mathcal{E}_{n_i} vary according to the concept;
4. run CDE, CDA, CDT and DL-Learner as a standard single concept learning approach for baseline comparison.
5. analyze the results achieved.

Towards encompassing the first step, we used the datasets *Kinship* and *Moral Reasoner*.

Each dataset was used to evaluate CDE, CDA and CDT from different perspectives. Therefore, a particular experimental methodology was used for each one, as described in the following section.

4.3.1 EXPERIMENTAL METHODOLOGY

With both datasets the description learning component chosen to learn the concepts was the DL-Learner system with default settings, since it is a largely used environment to learn DLs.

KINSHIP DATASET

Regarding this dataset, we want to investigate three issues: (i) whether the learned descriptions are according to the general semantics of the kinship domain; (ii) which approach yields the more readable and compact terminology; and (iii) whether the ordering of concepts defined beforehand makes some difference for the terminology learning task. Thus, we run and compare DL-Learner, as the approach for single concept learning, CDT, CDE and CDA. The latter considering three cases: (1) and (2) based on the definition of \mathcal{TL} and avoiding cycles: (1) the order established by CDE's taxonomy, in this case $\langle GP, GF, GM \rangle$ and (2) the reversed order of the one considered in (1) ($\langle GM, GF, GP \rangle$); (3) removing cycles.

MORAL REASONER

Concerning this dataset we want to investigate the following issues:

- i) how the completeness of the examples over the original set of individuals influences the proposed approaches? Towards answering this question we vary the training set considering 20%, 40%, 60%, 80% and 100% of examples.
- ii) what is the quality of the terminology learned by CDE, CDA and CDT, including a comparison with DL-Learner? We investigate this issue using quantitative and qualitative measures. For the former we considered f-measure while for the latter (1) the size, encompassing concepts, relations and constructors, and (2) the similarity to the original terminology. This last one we accomplished by subsumption relation: (a) does the learned terminology subsumes the original one (more general)? (2) does the original terminology subsumes the learned one (more specific)? If both questions are true, then the learned and original terminology are equivalent (this would be the best result possible).

Table 4.4: Toy Example results: Concepts Definitions and their sizes found with the methods CDE, CDA, CDT and DL-Learner (DL-L).

Approach	Concept	Definition	Size
DL-Learner	GP	EXISTS parent.EXISTS parent.TOP.	5
	GF	(male AND EXISTS parent.EXISTS parent.TOP).	7
	GM	(female AND EXISTS parent.EXISTS parent.TOP).	7
CDE	GP	EXISTS parent.EXISTS parent.TOP.	5
	GF	(grandparent AND male).	3
	GM	(grandparent AND female).	3
$CDA_{(1)}$	GP	(grandfather OR grandmother).	3
	GF	(male AND EXISTS married.grandmother).	5
	GM	(female AND EXISTS parent.EXISTS parent.TOP).	7
$CDA_{(2)}$	GP	EXISTS parent.EXISTS parent.TOP.	5
	GF	(grandparent AND male).	3
	GM	(grandparent AND female).	3
$CDA_{(3)}$	GP	EXISTS parent.EXISTS parent.TOP.	5
	GF	(grandparent AND male).	3
	GM	(grandparent AND female).	3
CDT	GP	EXISTS parent.EXISTS parent.TOP.	5
	GF	(grandparent AND male).	3
	GM	(grandparent AND female).	3

For this dataset 10-fold cross-validation was used.

4.3.2 EXPERIMENTAL RESULTS

In this section, the results obtained with the experiments are described.

KINSHIP DATASET

The results obtained considering the Kinship dataset is depicted in Table 4.4.

From that, it is possible to perceive that all concepts description follow the correspondent semantics. Moreover, CDE, CDA and CDT were able to learn a more compact and readable terminology than DL-Learner. Additionally, in order to uphold DL's assumption of acyclic terminologies we used: a version of CDA that avoids cycles ((1) and (2)), in this case orderings are particularly important, i.e., different orders entails different results; and a version of CDA that removes the cycles (3) (alg. 4 and 5). The results in Table 4.4 supports such conclusion and depicted that CDA avoiding cycles could achieve the same terminology as CDE and CDT by reversing its learning order.

MORAL REASONER DATASET

In the rest of this chapter we will refer to CDA avoiding cycles as CDA_1 or $CDA1$, and to CDA removing cycles as CDA_2 or $CDA2$.

Table 4.5 exhibits the results for all the proposed approaches (CDE, CDA_1 , CDA_2 and CDT), considering the two experiments (Exp1 and Exp2) described in Section 4.3.1 and the different percentage of training examples. The proportion of positive and negative examples was maintained in each set. Regarding CDE, we present the results for 3 different values of the threshold parameter (0.6, 0.8, 0.9). Moreover, to evaluate the approaches, we considered the percentage of original dependency among concepts found in the learned terminology (% Hits) and Table 4.5 depicts the average of the 10 folds.

Observing the results in Table 4.5, both CDE and CDA performed worse than expected. The CDA (1 and 2) behavior could be explained by it being even more sensitive to completeness than we expected, this might be the case since we direct 10% of the original examples for the evaluation fold in every scenario (so the real percentages of the original dataset are: 90%, 72%, 54%, 36% and 18%). To confirm this insight we executed the same scenarios in the whole original dataset (without cross validation).

Table 4.6 validated our solutions, showing that with the whole set of individuals CDA_1 was able to find all “hits” for Exp1. Furthermore, being the only approach able to achieve this. Moreover, the results for Exp2 was also improved. For Exp1 CDA_2 has a comparable result to the other approaches, but it is a lot better on Exp2, this might indicate that CDA_2 behaves better on more complex terminology learning problems. The results for CDE did not change as much as when the completeness was relaxed. Therefore, when all the individuals are known or when the examples are a more significant sample of the domain CDAs are the better choice. CDT’s approach found far less dependencies than its counterparts, Table 4.7 shows the CDT’s hits.

For the analysis of the terminology quality, DL-Learner was also considered.

Table 4.5: Aggregate Results of Relaxing Completeness Experiment for the methods CDE, CDA and CDT.

Approach	Experiment	Percentage	% Hits
CDE 0.9	exp1	100% (80%, 60%, 40%, 20%)	33% 0%
	exp2	100% 80% 60% 40% 20%	60% 80% 60% 40% 20%
CDE 0.8	exp1	100% (80%, 60%, 40%, 20%)	66% 0%
	exp2	100% 80% 60% 40% 20%	20% 80% 60% 40% 20%
CDE 0.6	exp1	100% 80% (60%, 40%, 20%)	66% 66% 0%
	exp2	100% 80% 60% 40% 20%	20% 20% 60% 40% 20%
CDA_1	exp1	100% (80%, 60%, 40%, 20%)	33% 0%
	exp2	(100%, 80%) 60% (40%, 20%)	20% 0% 0%
CDA_2	exp1	100% (80%, 60%, 40%, 20%)	33% 0%
	exp2	(100%, 80%) 60% (40%, 20%)	20% 0% 0%
CDT	exp1	(100%, 80%, 60%, 40%, 20%)	0%
	exp2	(100%, 80%, 60%, 40%, 20%)	0%

Table 4.6: Full Completeness over the individuals Experiment with the methods CDE, CDA and CDT.

Approach	Experiment	# Dependencies	% Hits
CDE(0.9, 0.8)	exp1	4	66%
	exp2	4	20%
CDE (0.6)	exp1	4	66%
	exp2	5	20%
CDA_1	exp1	3	100%
	exp2	6	40%
CDA_2	exp1	4	66%
	exp2	5	80%
CDT	exp1	0	0%
	exp2	0	0%

Table 4.7: Full Completeness Experiment CDT's Hits.

Coverage	Total		20%		40%		60%		80%		100%	
Fold	Exp		Exp		Exp		Exp		Exp		Exp	
	1	2	1	2	1	2	1	2	1	2	1	2
-	0	0										
1			0	0	0	0	0	0	0	0	0	0
2			0	0	0	0	0	0	0	0	0	0
3			0	1	0	0	0	0	0	0	0	0
4			0	0	0	0	0	0	0	0	0	0
5			0	0	0	0	0	0	1	0	0	0
6			0	0	0	0	0	0	0	0	0	0
7			0	0	0	0	0	0	0	0	0	0
8			0	2	1	0	0	0	1	1	0	0
9			0	0	0	0	0	0	0	0	0	0
10			0	0	0	0	0	0	1	0	0	0

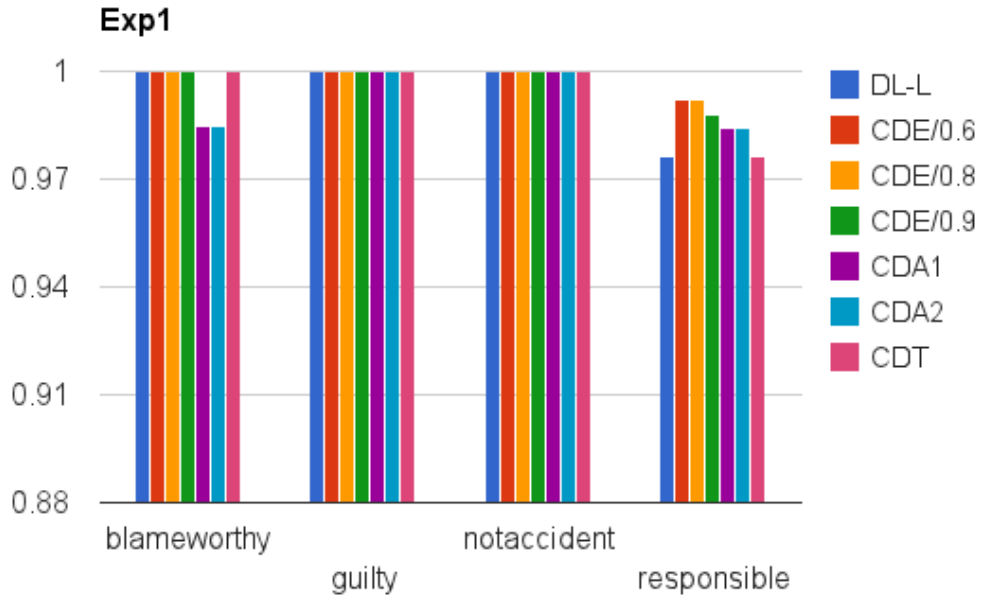


Figure 4.2: F-measure for Exp1 considering scenarios with CDE, CDA, CDT and DL-Learner (DL-L).

Fig. 4.2 and Fig. 4.3 plots the f-measure results for each of the concepts and for all scenarios. It is possible to notice that all approaches performed statistically similar in both Exp1 and Exp2, except CDA in Exp2, when inducing the definition of *weak_intend*. However, it is important to notice that in this specific case, the appropriate relationships was not considered (see Table 4.5), possibly because the lack of full completeness due to the 10% of examples reserved for validation, as discussed previously. Therefore, terminology learned with multiple concept learning approaches achieve similar predictive results compared to the single concept learning approach. This partially validates this research hypothesis: terminologies learned regarding dependencies among the concepts being learned have comparable quality (predictive power) to its counterpart learned with no regard for the dependencies.

Regarding the qualitative metrics, we used the whole set of examples. For the size of the found terminologies Fig. 4.4, on the far left we have the original size of the terminology, none of the approaches were equal or smaller than it. On the far right, we have the size for the terminologies without multiple concept learning, none of the approaches produced terminologies larger than it. CDT's results were

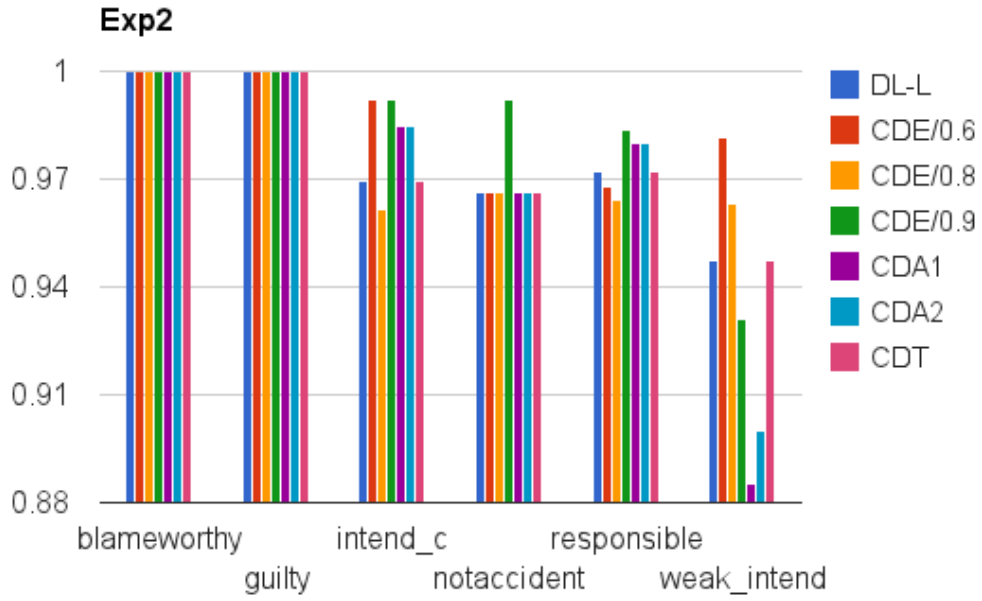


Figure 4.3: F-measure for Exp2 considering scenarios with CDE, CDA, CDT and DL-Learner (DL-L).

equal to DL-Learner’s because no redundancy was found. Apart from CDT, all the proposed methods induced far smaller terminologies than the equivalent concept learning without addressing the dependencies. This result partially validates this research hypothesis: if dependencies among the concept of the domain that need to be learned are found then *clearer* and *compact* terminologies are yield. In conjunction with the results related to the predictive power, this validates the research hypothesis: “ if dependencies among the concept of the domain that need to be learned are found then *clearer* and *compact* terminologies are yield wile their *quality* is maintained”.

For the size of concept per experiment see Fig. 4.5 and Fig. 4.6, the three CDE had very similar results, being consistently better or equivalent to DL-Learner, except on “responsible” in Exp1 and “notaccident” in Exp2. CDA_1 had the best result for “guilty” in Exp1, but its “blameworthy” was the worst among our approaches, exp. Interestingly, both CDA found by far the best result for “blameworthy” and “intend_c” in Exp2, with CDA_2 being even better, while being average in the other results. There is a trade-off on the size of the concepts, in some instances choosing

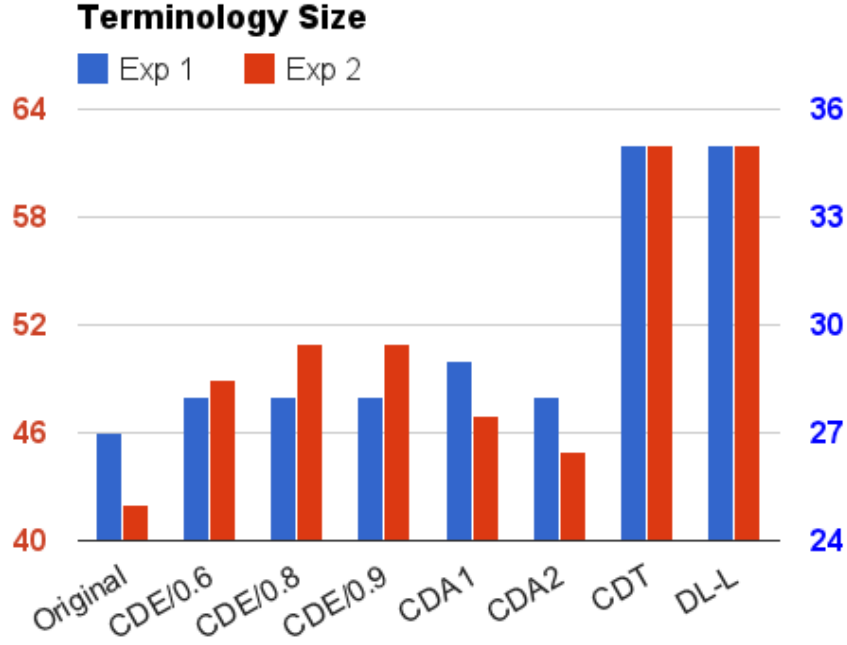


Figure 4.4: Size of found terminology for Exp1 and Exp2 with methods CDE, CDA, CDT and DL-Learner (DL-L).

a smaller definition for a concept affects the size of other related concepts, because the latter might not be able to use the former. This explains why CDA_2 had the best solutions overall, because different from the other approaches it tries alternative definitions for both concepts when a dependency incurs in a cycle.

Fig. 4.7 and Fig. 4.8 contrasts the size of concepts learned with their original definitions. The values are calculated through the formula $\frac{|originaldefinition|}{|learneddefinition|} - 1$, where values over 0 indicates that learned terminology is smaller than the original one. Most of the results were negative, with the size being between 40 to 70% bigger, while some results are positively better as “blameworthy” in Exp1 and “responsible” and “weak_intend” in Exp2, with definitions 200% smaller than the original ones. Additionally, a particularly important result is the performance of CDA concerning concept “blameworthy” in Exp2. It provides the higher decrease in size. Due to the fact that CDA uses assertions about all concepts being learned and “blameworthy” is the concept that is most dependent on other concepts from the learning task, it is the one that most benefits from CDA approach. On the other hand, CDE is the worst choice for this concept, since the taxonomy is more complex.

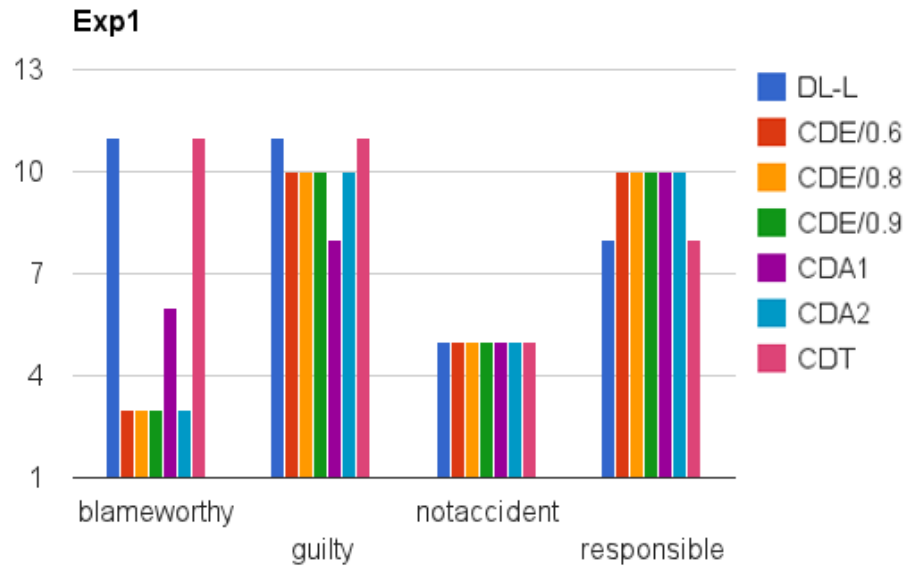


Figure 4.5: Size of concepts definitions for Exp1 with methods CDE, CDA, CDT and DL-Learner (DL-L).

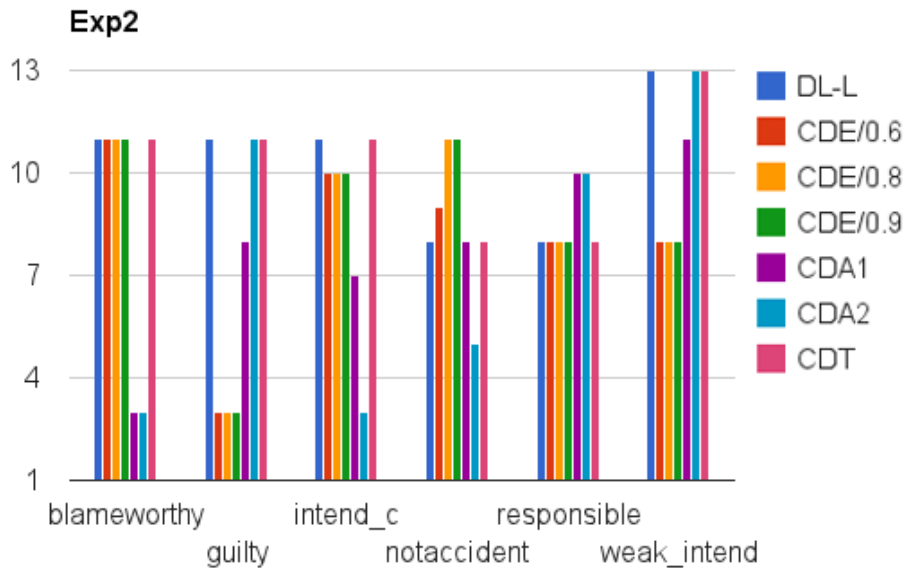


Figure 4.6: Size of concepts definitions for Exp2 with methods CDE, CDA, CDT and DL-Learner (DL-L).

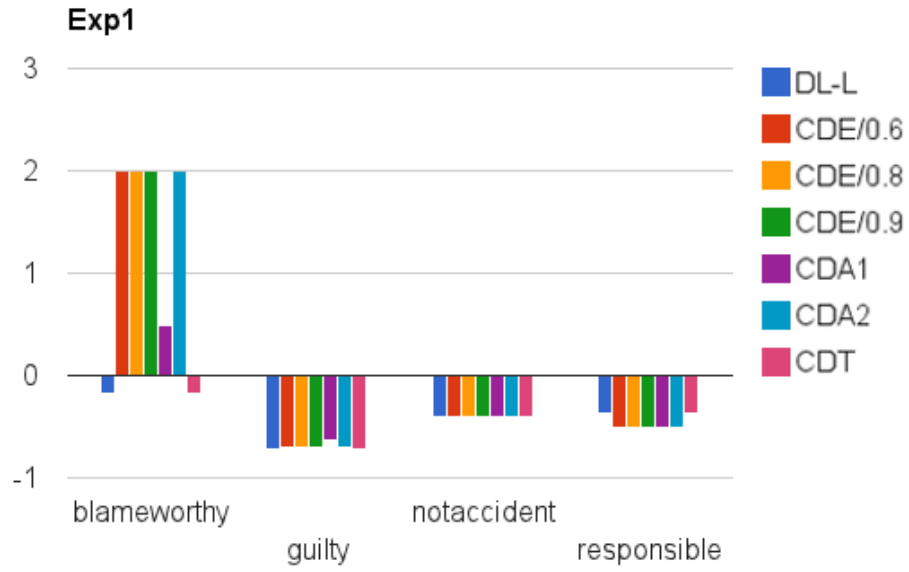


Figure 4.7: Size difference for Exp1 w.r.t. Original Definition with methods CDE, CDA, CDT and DL-Learner (DL-L).

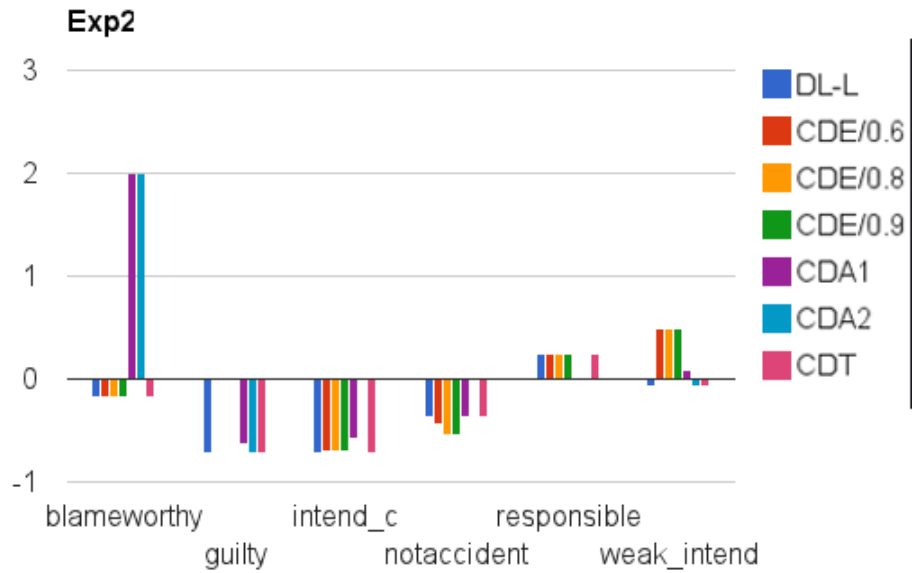


Figure 4.8: Size difference for Exp2 w.r.t. Original Definition with methods CDE, CDA, CDT and DL-Learner (DL-L).

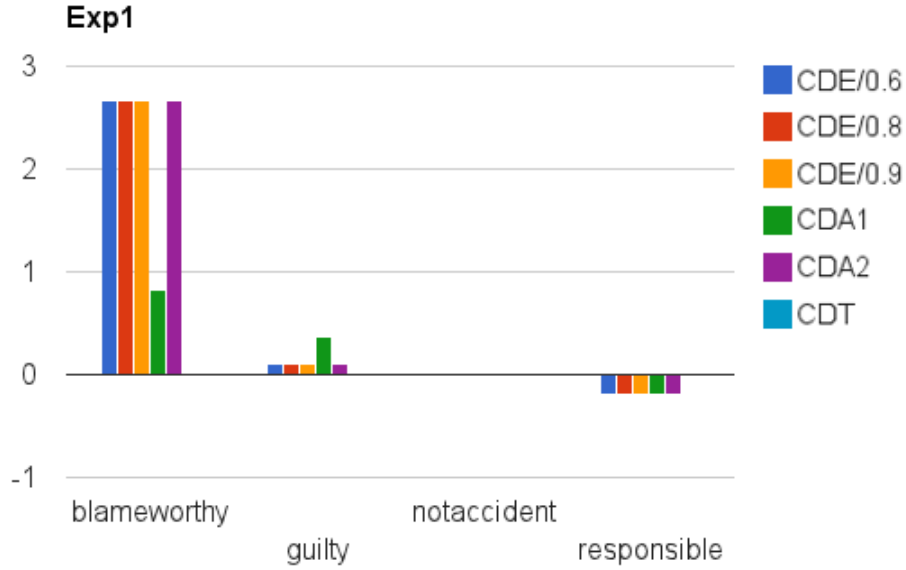


Figure 4.9: Size difference for Exp1 w.r.t. DL-Learner (DL-L) with methods CDE, CDA and CDT.

Fig. 4.9 and Fig. 4.10 uses the same formula, showing that CDEs and CDAs provide smaller definition than DL-Learner.

Furthermore, for Exp1 all the definitions learned subsumed the original definitions, while for Exp2 (i) definition for concepts {blameworthy, guilty, responsible} subsumes their original definition when DL-Learner and CDA are performed; (ii) definition for concepts {guilty, intend_c, weak_intend} subsumes their original definition when CDE is performed; (iii) the original definition for {notaccident} subsumes the definition learned with DL-Learner and (iv) the original definition for {notaccident, responsible} subsumes the learned definition when running CDA and CDE.

Summarizing, these results show the potential of the multiple concept learning approaches proposed in this work, to find smaller more readable solutions and, in some cases, solutions equivalent to those created by human beings, validating this research hypothesis. Furthermore, CDE proved to be less susceptible to the completeness assumption while CDA was very sensible to it. CDA_2 displayed a very good performance, being the closest to the original terminology on the more complex experiment (Exp2), however, one must not forget the additional cost of relearning the concepts to remove the cycles. Finally, CDT's approach found far less dependencies than its counterparts. This is due to the fact that syntactical substitutions

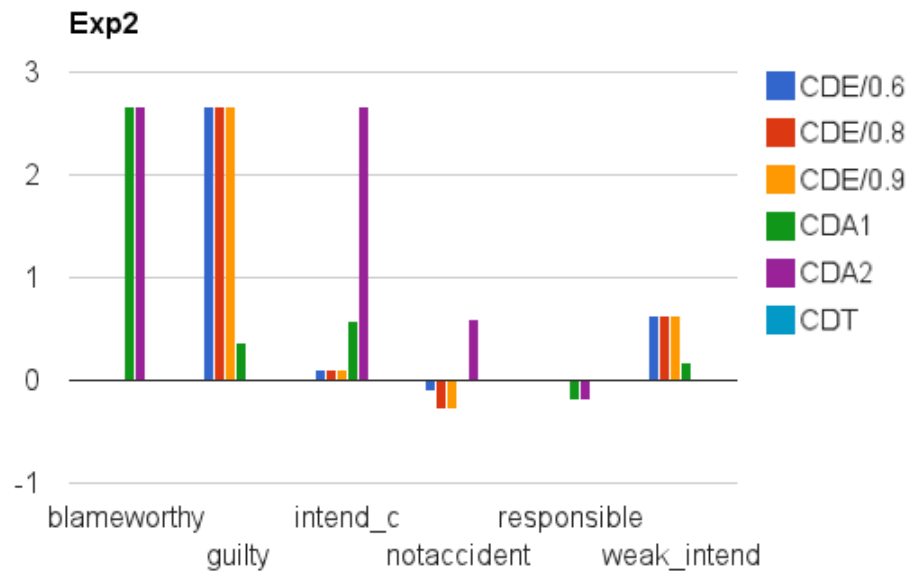


Figure 4.10: Size difference for Exp2 w.r.t. DL-Learner (DL-L) with methods CDE, CDA and CDT.

are far more unlikely when the set of concept learning problems have a wide range of possible solutions. This happens because the learner selects for short descriptions.

5 RELATED WORK

There are two distinct sets of related work, one regarding to the terminology learning problem (related to all three methods) and a set of related work particular to R2D2's use in theory restructuring.

5.1 TERMINOLOGY LEARNING

To the best of our knowledge, the literature related to terminology learning considering the induction of a set of related, but distinct concepts, is rather scarce. One seemingly related work is presented in (Distel, 2011), where relations among the concepts is discovered and represented through inclusion axioms (expressing a subsumption relation). Thus it is related to CDE, where the relation among concepts is represented through a taxonomy. However, Distel (2011) shares a goal with Baader et al. (2007) of finding the complete knowledge base for a DL, while we wish to deal only with a defined set of concepts.

Additionally, we can consider other works as related to ours assuming two perspectives: (i) single concept learning in DL, as such methods are used to learn the concepts definitions in all of the present methods and (ii) multiple predicates learning in ILP (Muggleton, 1991, 1992), as most of the theoretical background is shared between learning in DL and learning in ILP, and some interesting and useful ideas are bound to be shared between the two areas.

For the first case, the related works are DL-Learner (Lehmann and Hitzler, 2010), DL-FOIL (Fanizzi et al., 2008) or Yin-Yang (Iannone et al., 2007). As discussed in

Section 3, the main difference between them and our proposals is that the related work learn the terminology without looking into the relations existing among the concepts. Moreover, in Section 4, experiments showed that the proposed methods provide a smaller terminology compared to an approach of single concept learning.

In the second case, the most prominent related work is the one proposed in (De Raedt et al., 1993), where the problem of multiple predicate learning was defined as not limited to the generation of several independent predicate definitions but, rather involving the discovery of predicates dependencies. Although, this definition is very similar to the one defined in this master dissertation for our multiple concept learning approaches, specific implementations are required due to particular idiosyncrasies that emerge from the particular knowledge representation - descriptions logics and logic programming, in concept learning in DL and predicate (or concept) learning in ILP, respectively. Besides the particularities of the languages, the main difference between the approaches is that, while in (De Raedt et al., 1993) a set of predicates is learned in a interleaving way, with maybe more than one definition for each predicate, this cannot be done in DL according to the upheld assumptions (*“there is only one definition for a concept name”*).

In (Malerba et al., 1997) a definition for the problem of Multiple Concept Learning is defined, a solution using statistical functions to devise the dependency level on attribute-based domains and, finally, an ad-hoc method is proposed for multiple concept learning in FOL. The motivation and definition for the Multiple Concept Learning problem removing the independence assumption are very similar to the ones used in this work. The proposed method for Multiple Concept Learning on attribute-based domains are almost identical to CDE’s solution. It creates a graph (taxonomy) that models the dependencies among the concepts and a learning order is inferred from it, the dependencies are found using statistical methods such as χ^2 , but the idea that examples are the guides to the definitions is shared between CDE’s and the method used in (Malerba et al., 1997). However, the authors states that the statistical methods are not suitable for structure domain, as is the case with FOL

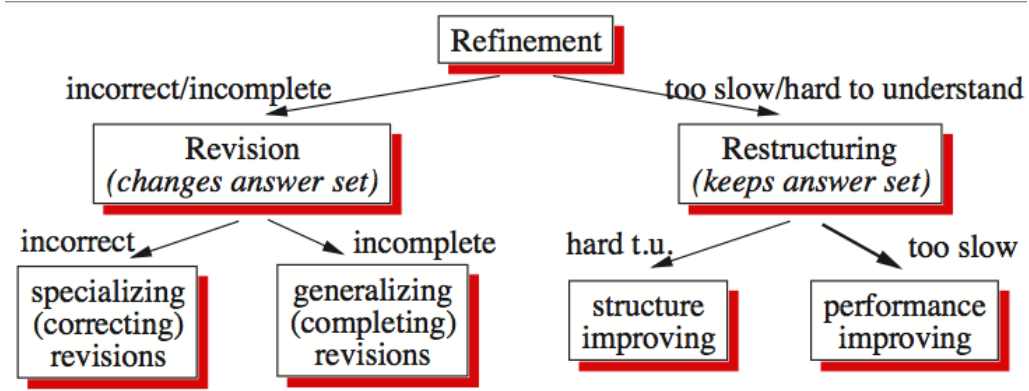


Figure 5.1: Taxonomy of theory refinement tasks (Wrobel, 1996).

and DLs. Lastly, an *ad-hoc* method for Multiple Concept Learning is presented and it suffers from the same problem of De Raedt et al. (1993) when transposing the ideas to the DL setting. Moreover, this method lacks any of the previous similarity with CDE's, because the graph defining the dependencies is not created within the learning process, on the contrary, it should be constructed by the user and be passed as a parameter to the method.

5.2 THEORY RESTRUCTURING - R2D2

In (Wrobel, 1996) there is a summary of works done in theory refinement for FOL. Theory refinement deals with the change of an existing theory to match a new external criteria, as oppose to learning new theories from scratch as it is done in ILP.

Because theory refinement makes changes on existing theories it can be seen as a knowledge base maintenance task. Theory refinement methods can be divided into theory revision and theory restructuring. The *revision* task changes the semantics of an existing theory in order to cope with new examples that are wrongly inferred. The *restructuring* task, on the other hand does not change the semantics of the theory, but it is intended either to increase the performance or the understanding of a theory. Figure 5.1 show a taxonomic overview of the refinement tasks.

R2D2 can be seen as a theory restructuring method for structure improving, i.e., understanding, to DLs. In this instance this proposed method might be used outside

the terminology learning problem.

Within this topic, FENDER’s (Sommer, 1995b) goal is the same as ours. FENDER is a method of *stratification* of theories, i.e., it structures a theory into layers of dependencies. It increases the number of layers, i.e., the dependencies within a theory. To do so, it uses an operator named *common partial premises*, which finds common groups of literals within the theory and creates new predicates from them thus increasing the dependencies while reducing redundancy. FENDER and R2D2 are similar in the sense that both have the same goal and a similar method. They differ because R2D2 does not create new concepts (predicates), i.e., the common groups can only be equal to an existing concept definition. Another theory restructuring system is PFORTE-PI (Revoredo et al., 2006, 2007), which uses the notion of predicate invention to restructure a probabilistic first-order theory, thus differing from R2D2 in the way the compression is made.

Additionally, there are two sets of works related to ours: i) tree representation of logical definitions, FOL (Fonseca et al., 2003) and DLs (Calvanese, 1996), and ii) tree isomorphism. In the former, their representation differs from ours in form, as their objective differs from ours. In general they use the tree representation to improve the scalability of reasoning. To that extend the structure is, at large, and ordered binary tree (in some cases the trees can have a larger degree). Because of the commutation of n-ary constructors we can not use ordered trees as a representation, as it would assume an order among the children, which is not suitable for syntactic compression.

Algorithm 9 presented in section 3.3.1 finds equivalent subtrees within a tree according to a matching tree. The equivalence of trees is well-known in the literature as *graph isomorphism* or more specifically *tree isomorphism*. Graph isomorphism is a NP-Complete problem (Read and Corneil, 1977), however in special cases it has polynomial solutions: trees are in this group of special cases (Bodlaender, 1990; Faulon, 1998; Buss, 1997; Messmer and Bunke, 1996; Shamir and Tsur, 1997). We leave the investigation of more efficient tree subgraph algorithms for future works.

6 CONCLUSIONS

This research showed three strategies for terminology learning considering the induction of related, but distinct concepts in the Description Logic setting. The first one, named CDE, automatically defines an order for learning the concepts, where this order is represented by a taxonomy tree of the concepts. This is accomplished by analyzing the taxonomic intersection of the examples sets associated to each concept. The second one, named CDA, does not require such an order for learning the collection of concepts. Instead, it assumes temporary assertions for all the other concepts that are not selected to be learned. As the concepts may be considered to be included in each other definition, we take an extra care to avoid definitions with cycles or to remove them. The third method, name CDT (R2D2), is applied after the terminology learning task is concluded. It substitutes sections by another concept, if the section is syntactically equivalent to the concept's definition. This allows for syntactical compression while maintaining the semantics. In all the cases, we expect that the returned terminologies are compact and readable descriptions of the concepts included in the domain of discourse.

In order to validate CDT for syntactic compression we used a set of 46 datasets. Among the datasets were some particularly large terminologies, one of them with over ten thousand concepts. We then went on to verify the relationship between the execution time and a terminology complexity. Analyzing the results, we concluded that the relationship is exponential but, as it seems, only prohibiting on very large terminologies, in the tens of thousands range; yet the method had reasonable execution times in the low tens of thousand: around 30 minutes for a terminology

with 10280 concepts. In terminologies with less than two thousand concepts we achieved runtime below the one minute mark. From the results, we came to the conclusion that using the proposed method is advisable with a upward soft limit of 10280 concepts.

We validated our methods by examining results yielded from two domains: a toy problem from the kinship domain and a more elaborated problem, denominated “moral reasoner”. Both of them are freely available in the DL-Learner package. In the first one, it was possible to observe that the terminology learned by CDE and CDA was more compact than the one learned with DL-Learner (standard SCL system). Moreover, CDA was more versatile than CDE. Analysing the second domain it was possible to observe that the threshold parameter for defining a proper relationship in CDE method gets more sensitive as the task is more complex. With a relatively simple task, varying this parameter did not provide significantly different results. Additionally, the completeness of individuals interferes in both CDE and CDA, the later being more sensible, i.e. varying the size of the training set, and as a consequence, the representativeness of the original individuals in the examples set of each concept, yield different quality of terminology. As both methods strongly rely on the set of examples to make crucial decisions, the closer from the original individuals are the assertions, the better the approaches will behave. Finally, the quantitative scores are only slightly affected by the different learning process and parameters. On the other hand, with the best selected threshold parameter and the closest set of individuals to the original task, all the methods, with exception of CDT, were able to fetch more compact and readable terminologies than the SCL. Both CDA’s methods outperformed all the other methods, especially CDA_2 on Exp2. However, this improved performance comes at a price, CDA_2 has to learn every alternative definitions in order to remove existing cycles. CDT’s approach found far less dependencies than its counterparts. This is due to the fact that syntactical substitutions are far more unlikely when the set of concept learning problems have a wide range of possible solutions. This happens because the learner selects for short

descriptions.

6.1 CONTRIBUTIONS

In this master dissertation we investigated the hypothesis that smaller terminologies can be induced when dependencies among the concepts that will be learned are considered, one of the main contributions of this work is the empirical corroboration of this claim.

In order to test the hypothesis we proposed three methods that utilize dependencies among concept to discover smaller and more comprehensible terminologies, they are:

- Concept Dependency through Examples (CDE);
- Concept Dependency through Assertions (CDA);
- Concept Dependency through Terminology (CDA).

Specific to CDA, we developed two alternative solutions that deal with the occurrence of cycles in the learned terminology: i) with cycle avoidance and ii) with cycle removal. These can be used when one is working under the assumption that terminologies are acyclic.

All the proposed methods were developed using the programming language Java and are available at <https://github.com/raphael-melo/mcl>, this is our main technical contribution.

To support our claims we developed, throughout this master dissertation, several arguments and definitions related to the task of learning multiple concept definitions, the value of simplifying terminologies and the use of the sets of examples as surrogates for a concept definition in the context of concept learning.

With regards to CDT, we proposed a representation for concept's descriptions using trees to deal with commutable constructors.

6.2 FUTURE WORK

An integral part of the terminology learning task involves learning a single concept definition, which is learned using one of the existing methods. As future work, a study of the underlying bias of this part of the process should be done, because each method has a slightly different focus, either on the general to specific direction (Lehmann and Hitzler, 2010; Fanizzi et al., 2008) or in the specific to general (Iannone et al., 2007) that may yields different results.

For CDT: i) Alternative more efficient algorithms for CDT tree isomorphism; ii) Allow the algorithms to find groups that are not a full concept definition, this will allow the generation of new concepts, and a greater syntactical compression.

Investigate methods to remove deeper cycles for CDA with cycle removal.

Further experiments on different domains are necessary. Also, an interesting questions is how the methods behave in datasets with noise.

On this research we intuitively assumed that the methods are language independent, in a future work other DL languages and probabilistic DLs (Revoredo et al., 2011) should be tested.

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Appendix A

OWA AND CWA AND THEIR RELATIONSHIP WITH INFERENTIAL AND INDUCTIVE REASONING

Usually *Closed World Assumption (CWA)* and *Open World Assumption (OWA)* are related with inferential knowledge (deductive knowledge), in this case:

Definition 9 (Closed World Assumption). *The truth-value of statements not currently known to be true is false.*

Definition 10 (Open World Assumption). *The truth-value of a statement is independent of whether or not it is currently known.*

When CWA is upheld, from Definition 9, an answer for a query can only be “True” or “False”, i.e., and statement is either a logical consequence or not (Example 12). Otherwise, when OWA is upheld, from Definition 10, an answer for a query can be “True”, “False” or “Unknown”, something is unknown when it: i) does not

contradict any of the conditions and ii) does not satisfy all the necessary conditions (Example 13).

Example 12. *Using the kinship domain with its default semantics. Have a individual $m1$ whose only known assertion is “male($m1$)”; and individual $f1$, whose only known assertion is “female($f1$)”. Let the concept definition for mother be: $mother \equiv female \sqcap \exists hasChild.\top$.*

When upholding CWA, it would produce the following answers:

mother($f1$)? False. mother($m1$)? False.

Example 13. *Using the kinship domain with its default semantics. Have a individual $m1$ whose only known assertion is “male($m1$)”; and individual $f1$, whose only known assertion is “female($f1$)”. Let the concept definition for mother be: $mother \equiv female \sqcap \exists hasChild.\top$.*

When upholding OWA, it would produce the following answers:

mother($f1$)? Unknown. mother($m1$)? False.

In the context of this work, we are dealing with inductive learning methods. In the inductive setting, one may see a connection between the closed or open assumption and the *Problem of induction*. The original problem of induction can be simply put. It concerns the support or justification of inductive methods. Inductive methods lack justification for either:

1. Generalizing the properties of a class of objects based on a finite number of observations of particular instances of a class (for example, the inference that “all swans seen so far are white, therefore all swans are white”, before a black swan is known) or
2. The uniformity of nature (Hume, 2000)

The CWA and OWA in the case of inductive learning are related to point 1, whether or not a inducted theory/terminology is justified based on the available examples. It has been argued in the past that such problem is unsolvable (Hume,

2000), i.e., there is no logical justification for generalization based on a finite set of examples (OWA). In practice this means that a learned theory/terminology should be only tentatively accepted while no new contradictory examples are presented, i.e., a theory is only correct with regards to a specific domain (CWA). Therefore, while using induction to learn a theory/terminology one is in practice using a type of CWA, in the sense that the induced theory/terminology is “only valid” on the learning domain, one cannot assert that a finite domain is representative of the universe.

Point 1 is also the reason behind the need of methods for theory revision.

One could also view a CWA and OWA with regards to the sets of examples for the induction of a theory/terminology. When learning a theory \mathcal{T}_i , using a background knowledge \mathcal{KB} and a set of examples \mathcal{E}_i , on the learning domain \mathcal{D}_l ; \mathcal{E}_i can be divided into:

- **Positives:** examples that should be covered by \mathcal{T}_i ;
- **Negatives:** examples that should not be covered by \mathcal{T}_i ;
- **Ignored:** examples that should not directly affect the inductive learning, but can either belong or not to \mathcal{T}_i .

If, for a domain \mathcal{D}_l , it is possible to enumerate all positive examples \mathcal{E}_{i_p} , the set of negative examples \mathcal{E}_{i_n} is the complement of \mathcal{E}_{i_p} w.r.t. \mathcal{D}_l . This is the case, because within the inductive learning method a individual either should be covered by the candidate hypothesis or it should not, if all the individuals that should be covered by \mathcal{T}_i are known all the others does not satisfy the requirements (w.r.t. \mathcal{D}_l) of \mathcal{T}_i . When this restriction is meet, this can be seen as under the CWA¹.

¹On CDE and CDA we are referring to this type of CWA.