Comenius university in bratislava Faculty of Mathematics, Physics and Informatics

ABDUCTION SOLVER BASED ON HIGHLY EFFICIENT C++ DL REASONER

Master thesis

Bc. Drahomír Mrózek

Comenius university in bratislava Faculty of Mathematics, Physics and Informatics



ABDUCTION SOLVER BASED ON HIGHLY EFFICIENT C++ DL REASONER

Master thesis

Study programme: Applied informatics

Field of study: 2511 Aplikovaná informatika

Study department: Department of Applied Informatics

Advisor: RNDr. Martin Homola, PhD.

Consultant: Mgr. Júlia Pukancová

Bratislava, 2017

Bc. Drahomír Mrózek

$t \wedge d$	lo:zadanie	
しひし	io.zauaine	

Čestne prehlasujem, že túto diplomovú prácu som vypracoval samostatne len s použitím uvedenej literatúry a za pomoci konzultácií u môjho školiteľa.

.....

Bratislava, 2017

Bc. Drahomír Mrózek

Acknowledgments

TODO

Abstract

This work will start from an existing solution of an abduction solver based on Pellet reasoner for description logics, implemented in Java. The implementation in C++ opens different ways for improvement and effectivization, starting with the utilization of a more effective C++ inference system for description logics.

Keywords: abduction, description logic

Abstrakt

Práca bude vychádzať z existujúceho riešenia abduktívneho systému založeného na reasoneri pre deskripčné logiky Pellet implementovaného v Jave. Pri implementácii v C++ sa otvárajú možnosti na zlepšenie a zefektívnenie existujúceho návrhu abduktívneho solvera, počnúc využitím efektívnejšieho C++ inferenčného systému pre deskripčné logiky.

Kľúčové slová: abdukcia, deskripčná logika

Contents

1	Intr	roduction	1	
2	Description logic			
	2.1	Introduction to description logic	2	
	2.2	Selected description logics	5	
		2.2.1 <i>ALC</i>	5	
		2.2.2 SHIQ	8	
		2.2.3 ALCHO	10	
		$2.2.4$ $\mathcal{SROIQV}(\mathcal{D})$	11	
	2.3	tableau algorithm	11	
3	Abo	duction	16	
	3.1	Abduction in description logic	18	
		3.1.1 ABox abduction	19	
	3.2	Uses	19	
4	\mathbf{Pre}	vious abduction solvers	20	
	4.1	theoretical approaches	20	
	4.2	implemented solutions	20	
5	Our	r approach	21	

C	CONTENTS	
	5.1 Our algorithm	25
6	Implementation	26
7	Results	29
8	Conclusion	30

Introduction

Story No. 1 TODO Úvod, troska kontextu, asi na 1,5 strany Cieľom práce je návrh a vývoj abduktívneho systému pre deskripčné logiky založený na existujúcom reasoneri s dôrazom na optimalizačné techniky a efektívnosť.

Description logic

2.1 Introduction to description logic

This chapter is based on Handbook on ontologies [7] and Handbook of knowledge representation [8].

The word "ontology" is used with different meanings in different communities. In philosophy, Aristotle in his Metaphysics defined **Ontology** as the study of attributes that belong to things because of their very nature.

Ontology focuses on the nature and structure of things independently of any further considerations, and even independently of their actual existence.

For example, it makes perfect sense to study the Ontology of unicorns and other fictitious entities: although they do not have actual existence, their nature and structure can be described in terms of general categories and relations.

in Computer Science, we refer to an **ontology** as a special kind of information object or computational artifact. Computational ontologies are a means to

formally model the structure of a system, that is the relevant entities and relations that emerge from its observation, and which are useful to our purposes. An example of such a system can be a company with all its employees and their interrelationships. The ontology engineer analyzes relevant entities and organizes them into concepts and relations, being represented, respectively, by unary and binary predicates.

Description logics (DLs) are a family of knowledge representation languages that can be used to represent an ontology in a structured and formally well-understood way. The "description" part of their name is based on how the important notions of the domain are described by concept descriptions (unary predicates) and atomic roles (binary predicates). The "logic" part comes from their formal, logic-based semantics, unlike some other methods of representation of ontologies, for example semantic networks.

Knowledge base (a set of facts) in description logics typically comes in two parts: a terminological part (TBox) and an assertional part(ABox).

TBox consists of general statements about concepts. Some examples,:

Example 2.1.1 [8] $HappyMan \equiv Human \sqcap \neg Female \sqcap (\exists married.Doctor) \sqcap (\forall hasChild.(Doctor \sqcup Professor)).$

This example defines a concept, 'HappyMan', as a human who is not female, is married to a doctor and his every child is a doctor or a professor.

Example 2.1.2 [8] $\exists hasChild.Human \sqsubseteq Human$

Or, in natural language, if someone has a child that is human, then they are human.

ABox consists of specific statements about individuals.

4

Example 2.1.3 /8/ bob : HappyMan

bob, mary: hasChild

 $mary : \neg Doctor$

This is an **ABox** of 3 statements: Bob is a happy man, Bob has a child - Mary, and Mary is not a doctor. You may notice that if we had a knowledge base consisting of TBox 2.1.1 and ABox 2.1.3, we may deduce that Mary must be a professor.

Interpretation of description logics is done using sets. We will formally define interpretations with specific description logics, but to informally make sense of previous examples:

Concepts can be interpreted as sets of constants,

individuals can be interpreted as constants,

relations as a set of pairs of constants,

 \sqcap as set conjunction \cap ,

 \sqcup as set disjunction \cup ,

 \neg as set complement,

 \sqsubseteq as subset symbol \subseteq ,

existential restriction $\exists \mathbf{r}.\mathbf{C}$ as a set of constants that are in relation \mathbf{r} with at least one individual in concept \mathbf{C} ,

and universal restriction \forall r.C as a set of constants that are not in relation r with any constant in complement of C.

Also, $A \equiv B$ means " $A \sqsubseteq B$ and $B \sqsubseteq A$ ".

2.2 Selected description logics

2.2.1 \mathcal{ALC}

In this thesis, we will be using a widely used description logic \mathcal{ALC} and it's extensions. \mathcal{ALC} stands for "Attributive concept Language with Complements". It's one of the less expressive languages, for example, it can't express the concept "someone who has 2 children". You can see examples of statements in \mathcal{ALC} in the previous section.

Definition 2.2.1 [8] (Syntax of \mathcal{ALC} concepts and roles). Let N_C be a set of concept names and N_R be a set of role names. The set of Concepts is the smallest set such that

- 1. \top, \bot , and every concept name $A \in N_C$ is an Concept,
- 2. If C and D are Concepts and $r \in N_R$, then $C \sqcap D$, $C \sqcup D, \neg C, \forall r.C, \text{ and } \exists r.C \text{ are Concepts.}$

 \top and \bot are special concepts 'everything' and 'nothing'. Every individual belongs to concept \top and no individuals belong to concept \bot .

The semantics of \mathcal{ALC} (and of DLs in general) are given in as interpretations.

Definition 2.2.2 [8] (\mathcal{ALC} semantics). An interpretation $\mathcal{I} = (\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}})$ consists of a nonempty set $\Delta^{\mathcal{I}}$, called the domain of \mathcal{I} , and a function $\cdot^{\mathcal{I}}$ that maps every \mathcal{ALC} Concept to a subset of $\Delta^{\mathcal{I}}$, and every \mathcal{ALC} role to a subset of $\Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$ such that, for all \mathcal{ALC} Concepts C, D and all role names r:

You may notice that nothing in the definition of interpretation says that an ontology must be 'true'. An interpretation which can intuitively be called 'true' for an ontology is called a model. We will now formally define it. An ontology in description logic is often called 'knowledge base'. It consists of various statements, in \mathcal{ALC} it consists of general concept inclusions (GCI), and assertional axioms. A set of GCIs are usually called a TBox (example ??) and a set of assertional axioms ABox(example 2.1.3).

Definition 2.2.3 [8] (ALC TBox model)

A general concept inclusion (GCI) axiom is of the form $C \sqsubseteq D$, where C, D are \mathcal{ALC} Concepts. An interpretation \mathcal{I} is a model of a GCI $C \sqsubseteq D$ if $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$.

 \mathcal{I} is a model of a TBox T if it is a model of every GCI in T.

Definition 2.2.4 [8] (ALC ABox model)

An assertional axiom is of the form x:C or (x, y):r, where C is an \mathcal{ALC} Concept, r is a role name, and x and y are individual names. An interpretation \mathcal{I} is a model of an assertional axiom x:C if $x^{\mathcal{I}} \in C^{\mathcal{I}}$, and \mathcal{I} is a model of an assertional axiom (x, y):r if $(x^{\mathcal{I}}, y^{\mathcal{I}}) \in r^{\mathcal{I}}$.

 \mathcal{I} is a model of an ABox A if it is a model of every assertional axiom in A.

Definition 2.2.5 [8] (Consistency)

 ${\mathcal I}$ is a model of a knowledge base ${\mathcal K}{=}(Tbox\;{\mathcal T},\;Abox\;{\mathcal A})$ if it's a model of ${\mathcal A}$ and ${\mathcal T}.$

If a model of K exists, we say that K is consistent.

An ontology can have multiple models, some less intuitive than other.

Example 2.2.1 (model)

```
Knowledge base K = \{T, A\}, T = \{T, A\}
       A \sqsubset B
      A \sqsubseteq \exists r.C
       C \sqsubseteq \forall r.D
}
\mathcal{A} = \{
       a:A
       c,d:r
One possible model of K, M_1, would be: {
      \Delta^{\mathcal{I}} = \{ a_x, c_x, d_x \}
      a^{\mathcal{I}} = a_x, c^{\mathcal{I}} = c_x, d^{\mathcal{I}} = d_x
      A^{\mathcal{I}} = \{a_x\}, B^{\mathcal{I}} = \{a_x\}, C^{\mathcal{I}} = \{c_x\}, D^{\mathcal{I}} = \{d_x\}
      r^{\mathcal{I}} = \{ \langle a_x, b_x \rangle, \langle a_x, c_X \rangle, \langle c_x, d_x \rangle \}
But other models also exist, for example \mathcal{M}_2 and \mathcal{M}_3. \mathcal{M}_2 = \{
      \Delta^{\mathcal{I}} = \{ a_x, c_x, d_x, c_n \}
      a^{\mathcal{I}} = a_x, c^{\mathcal{I}} = c_x, d^{\mathcal{I}} = d_x
      A^{\mathcal{I}} = \{a_x\}, B^{\mathcal{I}} = \{a_x\}, C^{\mathcal{I}} = \{c_n\}, D^{\mathcal{I}} = \{\}\}
```

$$r^{\mathcal{I}} = \{\langle a_x, b_x \rangle, \langle a_x, c_n \rangle, \langle c_x, d_x \rangle \} \}$$

$$\mathcal{M}_3 = \{$$

$$\Delta^{\mathcal{I}} = \{i_x\}$$

$$a^{\mathcal{I}} = i_x, c^{\mathcal{I}} = i_x, d^{\mathcal{I}} = i_x$$

$$A^{\mathcal{I}} = B^{\mathcal{I}} = C^{\mathcal{I}} = D^{\mathcal{I}} = \{i_x\}$$

$$r^{\mathcal{I}} = \{\langle i_x, i_x \rangle \}$$

$$\}$$

2.2.2 SHIQ

 \mathcal{SHIQ} is one of the most expressive description logics. S - abbreviation of \mathcal{ALC} with transitive roles.

 \mathbf{H} - Role hierarchy (role r_1 can be subrole of role r_2)

I - Inverse properties (if a,b : r, then b,a : r^-)

Q - Quantified cardinality restrictions (for example $\leq 2hasChild$)

Examples of Concepts in SHIQ:

Example 2.2.2 [7] Examples of Concepts in SHIQ:

 $Human \sqcap \neg Female \sqcap \exists married. Doctor$

 $\sqcap (\geq 5hasChild) \sqcap \forall hasChild.Professor$.

"A man that is married to a doctor and has at least five children, all of whom are professors".

 $Human \sqsubseteq \forall hasParent.Human \sqcap (\geq 2hasParent.\top)$

 $\sqcap (\leq 2hasParent.\top) \sqcap \forall hasParent^-.Human$

"If someone is a human, all their parents are human, they have exactly two parents, and everything that has them as a parent (i.e. is their child) is a human."

 $hasParent \sqsubseteq hasAnccestor.$

"hasParent is a subrole of hasAncestor (i. e. If A hasparent.B, then A hasAncestor.B)."

Trans(hasAncestor)

"The role has Ancestor is transitive (i.e. if A has Ancestor. B and B has Ancestor. C then A has Ancestor. C)."

The definitions of syntax and semantics of SHIQ are similar to those of ALC.

Definition 2.2.6 [7] (SHIQ concept and role syntax) Let R be a set of role names, which is partitioned into a set R_+ of transitive roles and a set R_p of normal roles. The set of all SHIQ roles is $R \cup \{r^- | r \in R\}$, where r^- is called the inverse of the role r.

Let C be a set of concept names. The set of SHIQ concepts is the smallest set such that:

- 1. every concept $A \in C$ is a SHIQ concept.
- 2. if A and B are SHIQ concepts and r is a SHIQ role, then $A \sqcap B, A \sqcup B, \neg A, \forall r. A, and \exists r. A \text{ are SHIQ concepts.}$
- 3. if A is a SHIQ concept and r is a simple SHIQ role (simple role is neither transitive nor has a transitive subrole), and $n \in \mathbb{N}$, then $(\leq nr.A)$ and $(\geq nr.A)$ are SHIQ concepts.

 \mathcal{SHIQ} semantics can be described as \mathcal{ALC} semantics with same additions.

Definition 2.2.7 (SHIQ semantics) [7] in addition to definition ??, for all $p \in R$ and $r \in R_+$:

 $\langle x, y \rangle \in p^{\mathcal{I}} \text{ iff } \langle y, x \rangle \in (p^{-})^{\mathcal{I}}.$

if
$$\langle x, y \rangle \in r^{\mathcal{I}}$$
 and $\langle y, z \rangle \in r^{\mathcal{I}}$ then $\langle x, z \rangle \in r^{\mathcal{I}}$.

$$(\leq nr.C)^{\mathcal{I}} = \{ x \in \Delta^{\mathcal{I}} | \#r^{\mathcal{I}}(x, C) \leq n \},$$

$$(\geq nr.C)^{\mathcal{I}} = \{ x \in \Delta^{\mathcal{I}} | \#r^{\mathcal{I}}(x, C) \geq n \},$$

where #M denotes the cardinality of the set M, and $r^{\mathcal{I}}(x,C) := \{y | \langle x,y \rangle \in r^{\mathcal{I}} \text{ and } y \in C^{\mathcal{I}} \}.$

SHIQ ABox and it's model are the same as in ALC (definition 2.2.4). For the TBox, we have to add role subsumption axioms. Some authors define TBox as only containing GCIs, and use a new structure, RBox, to contain role inclusions. For this thesis, role inclusion axioms are a part of TBox.

Definition 2.2.8 [7] (SHIQ TBox)

A role inclusion axiom is of the form $r \sqsubseteq s$, where r, s are roles. An interpretation \mathcal{I} is a model of a role inclusion axiom $r \sqsubseteq s$ if $r^{\mathcal{I}} \subseteq s^{\mathcal{I}}$.

 \mathcal{I} is a model of a TBox \mathcal{T} if it it is a model of every role inclusion axiom and GCI axiom (definition ??) in TBox.

2.2.3 ALCHO

ALC with role hierarchy and Nominals.

Nominals are concepts with exactly one specific instance. For example, {john} is a concept with its only instance being the individual 'john'.

Nominals can be used to express enumerations, for example [3]:

$$Beatle \equiv \{john\} \sqcup \{paul\} \sqcup \{george\} \sqcup \{ringo\}$$

Role hirerarchy was already described in section 2.2.2 (example ??).

Definition 2.2.9 (Syntax and semantics of ALCHO)

Syntax of ALCHO is the syntax of ALC (definition 2.2.1), with $\{a\}$ added

to the set of concepts C for each individual 'a'.

Similarly, semantics of ALCHO are the semantics of ALC (definition 2.2.2) with the addition of $\{a\}^{\mathcal{I}} = \{a^{\mathcal{I}}\}\$,

where 'a' is an individual and \mathcal{I} is the interpretation.

In \mathcal{ALCHO} , the definition of an ABox is the same for \mathcal{ALC} (definition 2.2.4) and the definition of a TBox is the same as for \mathcal{SHIQ} (definition 2.2.8.

2.2.4 $\mathcal{SROIQV}(\mathcal{D})$

Jazyk koncludu, TODO asi ked bude hotova implementacia.

2.3 tableau algorithm

In our algorithm, we heavily make use of tableau algorithm. Tableau algorithm is a method of constructing a model of a knowledge base \mathcal{K} if \mathcal{K} is consistent, and stops if no model of \mathcal{K} exists and therefore \mathcal{K} is inconsistent.

Tableau algorithm uses knowledge base in negation normal form (NNF), that is, every concept complement \neg applies only to a concept name [8]. Any \mathcal{ALC} concept can be transformed to an equivalent concept in NNF by using de Morgan's laws and the duality between existential and universal restrictions ($\neg \exists r.C \equiv \forall r. \neg C$). For example, the concept $\neg (\exists r.A \sqcap \forall s.B)$, where A, B are concept names, can be transformed using de Morgan's laws to $\neg \exists r.C \sqcup \neg \forall s.B$, and this can then be transformed using the existential-universal duality into ($\forall r. \neg A$) \sqcup ($\exists s. \neg B$).

The idea behind the tableau algorithm for $\mathcal{K} = \{\mathcal{T}, \mathcal{A}\}$ is to start with the concrete situation described in \mathcal{A} and expand based on what can be

inferred from \mathcal{T} and currently known ABox statements. This is done using something called completion graph, which is a graph where nodes represent individuals, directed edges represent relations between individuals, each node has a label containing concepts the individual belongs to, and each edge has a label consisting of the names of it's roles.

Definition 2.3.1 (Completion graph)

A completion graph is a pair (G, \mathcal{L}) , where G is a directed finite graph and \mathcal{L} is a labeling function mapping each node from G to a set of concepts, and each edge to a set of roles.

Tableau algorithm for $\mathcal{K}(\mathcal{T}, \mathcal{A})$ first creates a completion graph based on \mathcal{A} , and then expands it using tableau expansion rules.

Definition 2.3.2 [8] (ALC tableau expansion rules)

- \sqcap -rule: if $C_1 \sqcap C_2 \in \mathcal{L}(x)$, x is not blocked (definition 2.3.4), and $\{C_1, C_2\} \not\subseteq \mathcal{L}(x)$ then set $\mathcal{L}(x) = \mathcal{L}(x) \cup \{C_1, C_2\}$
- \sqcup -rule: if 1. $C_1 \sqcup C_2 \in \mathcal{L}(x)$, x is not blocked, and $\{C_1, C_2\} \cap \mathcal{L}(x) = \emptyset$, then set $\mathcal{L}(x) = \mathcal{L}(x) \cup \{C\}$, for some $C \in \{C_1, C_2\}$
- \exists -rule: if $\exists r.C \in \mathcal{L}(x)$, x is not blocked, and x has no r-successor y with $C \in \mathcal{L}(y)$, then create a new node y with $\mathcal{L}(\langle x, y \rangle) = \{r\}$ and $\mathcal{L}(y) = \{C\}$.
- \forall -rule: if $\forall r.C \in \mathcal{L}(x)$, x is not blocked, and there is an r-successor y of x with $C \notin \mathcal{L}(y)$ then set $\mathcal{L}(y) = \mathcal{L}(y) \cup \{C\}$.
- \sqsubseteq -rule: if $C_1 \sqsubseteq C_2 \in \mathcal{T}$, x is not blocked, and $C_2 \sqcup NNF(\neg C_1) \notin \mathcal{L}(x)$, then set $\mathcal{L}(x) = \mathcal{L}(x) \cup \{C_2 \sqcup NNF(\neg C_1)\}$

Where C, C_1, C_2 are concepts, r is role, \mathcal{T} is TBox, and NNF is normal negation form.

Why are we checking whether nodes are blocked? And what are blocked nodes?

If we removed "x is not blocked" from all expansion rules, then the algorithm could generate an infinite graph using the \exists rule, for example for $\mathcal{K} = (\mathcal{T}, \mathcal{A}), \mathcal{T} = \{C \sqsubseteq \exists r.C\}, \mathcal{A} = \{a : C\}$ the algorithm would create a node a_2 with $\langle a, a_2 \rangle : r$, then a node a_3 with $\langle a_2, a_3 \rangle : r$ and so on. To guarantee termination, we define node blocking.

Definition 2.3.3 (ancestor) In completion graph $CG = (G, \mathcal{L}), G = (N, E),$ nodes $x, y \in N$, and edge $\langle x, y \rangle \in E$, then y is a successor of x and x is an ancestor of y.

If $\mathcal{L}(\langle x, y \rangle) = r$, then y is an r-successor of x.

Ancestry is transitive (if node x is an ancestor of node y and y is an an ancestor of node z, then x is is an ancestor of z).

Definition 2.3.4 (blocking) A node x is blocked if it has an ancestor y that is either blocked, or $\mathcal{L}(x) \subseteq \mathcal{L}(y)$.

And now we can show the pseudocode of (nondeterministic) tableau algorithm.

Definition 2.3.5 (clash)

In completion graph $\mathcal{CG} = ((N, E), \mathcal{L})$, if there is a node $n \in N$ and a concept C where $\{C, \neg C\} \in \mathcal{L}(n)$, then \mathcal{CG} has a clash.

If the algorithm cannot apply any expansion rules, then K is consistent and \mathcal{CG} is its model, or a finite part of an infinite model due to blocking. Our

```
1: function TABLEAUALG( Knowledge base \mathcal{K} = (\mathcal{T}, \mathcal{A}))
         Convert \mathcal{T} to NNF.
 2:
         Completion graph \mathcal{CG} = (G, \mathcal{L}), G = (N, E), N = E = \mathcal{L} = \emptyset
 3:
         for Each individual i \in \mathcal{A} do
 4:
              N = N \cup n_i
 5:
              for Each assertional axiom (i:C) \in \mathcal{A} do
 6:
                   \mathcal{L}(n_i) = \mathcal{L}(n_i) \cup C
 7:
 8:
              end for
              for Each assertional axiom (i, x : r) \in \mathcal{A} do
 9:
                   E = E \cup \langle n_i, n_x \rangle
10:
                   \mathcal{L}(\langle n_i, n_x \rangle) = \mathcal{L}(\langle n_i, n_x \rangle) \cup r
11:
              end for
12:
         end for
13:
         while A tableau expansion rule can be applied on \mathcal{CG} do
14:
15:
              Apply a rule on CG
              if Clash exists in \mathcal{CG} then
16:
                                 "\mathcal{K}
                                          is
                                                 inconsistent"
                                                                       (assuming
                                                                                         algorithm
                   return
17:
     undeterministically always picks the 'correct' decision in ⊔ rule if
     one exists)
              end if
18:
         end while
19:
20:
         return "\mathcal{K} is consistent"
21: end function
```

abduction algorithm only needs this finite part.

The tableau algorithm has 2 sources of nondeterminism: picking which rule to apply, and how to apply the \sqcup rule. The order of rule applications doesn't matter for the sake of determining consistency, but the application of the \sqcup rule does, as one choice can lead to a clash while the other not.

If a clash happens in a deterministic implementation, we can backtrack to a previous \sqcup decision with an unexplored choice and continue from there. If there are no unexplored \sqcup decisions and we find a clash, \mathcal{K} is inconsistent (no model exists). If there is no decision with an unexplored possibility we can backtrack to, we can declare \mathcal{K} to be inconsistent. I think it would be useful to show an example of tableau completion graph:

obrazok odstraneny, nejake problemy s hboxom a nemoznostou lomit riadok.

Abduction

Logical thinking can be divided into 3 categories: **Deduction**, **Induction** and **Abduction**.

Deduction is the process of using known causes and rules to infer the results of a rule. For example, if we know the fact that a floor is wet, and the rule that this particular floor is slippery when wet, we can arrive at a conclusion that the floor must be slippery. Deduction is the only one of the 3 types of logical reasoning where if the premises are true and the rules used are true, then the conclusion must also be true.

Induction is the process of knowing the cause and effect and creating a plausible rule. For example, we know that whenever we've seen this floor wet, it was also slippery, therefore, the floor is slippery when wet. Unlike deduction, induction the result of induction isn't necessarily correct.

Abduction, also known as hypothesis or diagnosis, is when we know the rules and observe an unexpected effect, and try to find an explanation for it - a plausible cause. For example, we if we see someone slip on the floor and know that the floor is slippery when wet, we may assume that the floor

CHAPTER 3. ABDUCTION

17

patients symptoms, knows which diseases cause which symptoms, and based

is wet. Another example of abductive reasoning is when a doctor observes

on these rules guess which disease the patient may have. Like with induction,

there are often multiple plausible explanation, and the true explanation may

not be among them even if all the information we have is correct; the person

who slipped on the floor may have slippery shoes, or the patient could have

a new diease unknown to the doctor.

If the only condition for \mathcal{E} being an abductive explanation for observation O

in knowledge base \mathcal{K} was that $\mathcal{K} \sqcup \mathcal{E} \models O$, we would reach some unintuitive

explanations, for example for O="The floor is slippery" and $\mathcal{K}=$ "The floor is

slippery when wet", \mathcal{E} could be "The floor is slippery" (as in first order logic

 $A \to A$) or "The sun is shining and the sun is not shining" $(\neg A \to A \to B)$

or "The floor is wet and a bird is chirping" (irrelevant information). To limit

ourselves only to more useful explanations, we will also add some restrictions

to our definition of logical abduction for the purpose of our work:

Definition 3.0.1 (Abductive explanation) [1]

Set of axioms \mathcal{E} is an explanation of observation O in knowledge base \mathcal{K} , iff:

• $\mathcal{K} \cup \mathcal{E} \models O$

• Consistency : $\mathcal{K} \cup \mathcal{E} \not\models \bot$

• Relevance : $\mathcal{E} \not\models O$

• Explanatoriness : $\mathcal{K} \not\models O$

• Minimality: There is no other explanation \mathcal{F} of O in \mathcal{K} , where $\mathcal{F} \subset \mathcal{E}$

(TODO: v elsenbroich namiesto \cup je +, myslim ze tu sa asi viac hodi \cup

ale niesom si isty)

From our previous example, "The floor is slippery" is not an explanation due to the relevancy condition, "The sun is shining and not shining" due to the consistency condition, and "The floor is wet and a bird is chirping" because of the minimality condition, while "The floor is wet" fulfills all the conditions and therefore is an explanation of O.

If the K was "The floor is slippery when wet and the floor is wet" and was "The floor is slippery", there would be no explanation due to the explanatoriness condition - the observation can already be inferred from the knowledge base using deductive reasoning.

3.1 Abduction in description logic

Elsenbroich et. al. [1] defined several types of abduction in description logic: TBox abduction, ABox abduction and Concept abducion. We are mainly interested in the ABox abduction.

TBox abduction is the process of finding a finite set of TBox rules \mathcal{S}_t for knowledge base \mathcal{K} and concepts \mathcal{C}, \mathcal{D} satisfiable w.r.t. \mathcal{K} , so that $\mathcal{K} \cup \mathcal{S}_t \models \mathcal{C} \sqsubseteq \mathcal{D}$. This type of abduction is used for ontology debugging: If an ontology engineer expects $\mathcal{C} \sqsubseteq \mathcal{D}$ to follow from \mathcal{K} but finds it doesn't, they can look for TBox rules to add to \mathcal{K} . On the other hand, if an undesirable $\mathcal{C} \sqsubseteq \mathcal{D}$ follows from the ontology, they can find such \mathcal{S}_t from \mathcal{K} so that $\mathcal{K} - \mathcal{S}_t \not\models \mathcal{C} \sqsubseteq \mathcal{D}$. (TODO: je - spravny vyraz? a ake je vlaste previdlo pre to kde vsade ma ist mathcal?)

TODO: Concept abduction

TODO: co povedat o knowledge base abduction abduction?

19

3.1.1 ABox abduction

In ABox abduction, we are looking for an explanation \mathcal{E} of observation O in knowledge base \mathcal{K} according to rules 3.0.1, where both \mathcal{E} abd O are limited to ABox axioms.

For example, for a simple ontology where the Abox of the knowledge base is empty and the Tbox= $\{\mathcal{A} \sqsubseteq \mathcal{C}; \mathcal{B} \sqsubseteq \mathcal{C}\}$, and an observation Abox= $\{a:\mathcal{C}\}$, there are explanations: $\{\{a:\mathcal{A}\}, \{a:\mathcal{B}\}\}. \{a:\mathcal{C}\}$ is not an explanation due to the relevancy requirement, $\{a:\mathcal{A},a:\mathcal{B}\}$ is not and explanation due to the minimality requirement.

TODO: relevancy testing in ABox abduction without using reasoner (dat to sem alebo do implementacie?)

TODO uses: automatic planning, medical (paper)

TODO: Abduction as set cover, abduction as probability

3.2 Uses

TODO: Medical, automatic code checking, automatic planning, any type of diagnosis

Previous abduction solvers

theoretical approaches 4.1

TODO: abdukcia v FOL TODO: bol nejaky pokus o abdukciu v deskripcnej

logike nezalozeny na hitting setoch? - ten co som nasiel na mobile by sa

mozno dal spomenut, nepouziva termin "hitting set", pouziva substitucie na

uzatvaranie tableaux s dvojitymi labelmi '

implemented solutions 4.2

TODO: Racer

20

Our approach

The approach most often used to perform abductive reasoning in description logic without translating to other formal logics is based on the following approach: Let there be a knowledge base \mathcal{K} , observation O, and a set of axioms \mathcal{S} . If $\mathcal{K} \sqcup \mathcal{S}$ is consistent, then by definition there is at least one model of $\mathcal{K} \sqcup \mathcal{S}$. If $\mathcal{K} \sqcup \mathcal{S} \sqcup \neg O$ is inconsistent, then there is no model for $\mathcal{K} \sqcup \mathcal{S}$ where $\neg O$ is not true, that is every model of $\mathcal{K} \sqcup \mathcal{S}$ contains O, so $\mathcal{K} \sqcup \mathcal{S} \models O$.

We can find such a set S by generating every model of $K \sqcup \neg O$, and picking a set of complements of axiom in these models so that every model has at least one axiom complement in S. This can be formulated as the hitting set (defined below 5.0.1) problem (which is equivalent to the set cover problem) - for each model in the set of models M of $K \sqcup \neg O$, we create an **antimodel** (5.0.2)consisting of negations of every axiom in the model, the set of these antimodels we call M'. Our goal is finding a minimal (inclusion-wise) set S containing at least one axiom from each antimodel in M' - S a hitting set 5.0.1 for M'.

Additionally, if S is relevant and explanatory (??) and $K \sqcup S$ is consistent, it's an explanation for observation O.

Definition 5.0.1 (Hitting set (TODO: cituj paper))

A hitting set for a collection of sets F (in our case, F is the collection of antimodels) is a set H s.t. $H \cap S \neq \{\}$ for every $S \in F$. A hitting set H for F is minimal if there is no other hitting set H' for F s.t. $H' \not\subseteq H$.

Definition 5.0.2 To better explain our algorithm, it will be useful to define the term 'antimodel'. Let M be a model of knowledge base K. Then M' is an antimodel of K iff it contains negations of every axiom from M and nothing else - for every axiom of form a:C in M, M' has $a:\neg C$, and for every axiom a,b:R in M it has $a,b:\neg R$ (a and b are not in role R). (TODO: toto asi pre niektore deskripcne logiky nieje mozne vyjadrit, (role complements))

This idea was first introduced by Raymond Reiter in "A Theory of Diagnosis from First Principles" [5] as a general method for abductive reasoning in any formal logic with binary semantics (every statement is either true or false) and operands \land , \lor , \neg with their usual semantic meaning, including first order logic. Additionally, Reiter proposes using a hitting set tree, which we will describe later.

Ken Halland and Katarina Britz in "ABox abduction in ALC using a DL tableau"[2] proposed an algorithm using the idea of hitting sets for abduction in description logic ALC, using a modified tableaux algorithm - their algorithm first develops all possible completion graphs (multiple graphs resulting from the use of \Box rule), based on the knowledge base, and once there are no more rules to apply, they add an axiom from the observation complement $\neg O$ to the knowledge base. If there is no rule to apply or unused

observation, the model is added to the list of models from which minimal hitting set is generated.

This algorithm generates every model reachable by tableaux algorithm for $\mathcal{K} \sqcup O$, which as we will show, is not necessary.

Our work is mainly based on the algorithm by Martin Homola and Júlia Pukancová, using the idea of a hitting set tree from Reiter [5], which make generating every model of $\mathcal{K} \sqcup \neg O$ not necessary.

Definition 5.0.3 (Hitting set tree (TODO: reference)) A hitting set tree (HS-tree) for a collection of sets F is T=(V, E, L, H), where (V, E) is the smallest tree in which the labelling function L labels the nodes of V by elements of F, the edges of E by elements of sets in F, and H(n) is the set of edge-labels from the root node to $n \in V$, s.t.:

- (a) for the root $r \in V$: L(r) = S for some $S \in F$, if $F \neq \{\}$, otherwise $L(r) = \{\}$;
- (b) for each $n \in V$: L(n) = S for some $S \in F$ s.t. $S \cap H(n) = \{\}$, if such $S \in F$ exists, otherwise $L(n) = \{\}$;
- (c) each $n \in V$ has a successor n_{σ} for each $\sigma \in L(n)$ with $L(n, n_{\sigma}) = \sigma$.

We can generate the HS-tree inf the following way: let F be the list of antimodels for $\mathcal{K} \cap \neg O$. The label of each vertex n is either an antimodel of $\mathcal{K} \cap H(n) \cap \neg O$ (which is also an antimodel of $\mathcal{K} \cap \neg O$) or empty, if no such model exists - in this case H(n) is a hitting set of F, and $\mathcal{K} \cap H(n) \models O$ - H(n) is an explanation of H(n) if it also fulfills the other conditions (??). If the vertex n is labeled by an antimodel, we create a child vertex for each axiom of antimodel L(n) - we label the edge by that axiom.

By using a HS-tree, we can find a hitting set that hits every antimodel of $\mathcal{K} \cap \neg O$ while having to generate only a few of these models - each choice of edge label usually also eliminates many models that were not generated. The H and P (TODO ref) algorithm uses this algorithm, combined with the pruning methods (for example, eliminate a vertex n if H(n) contains axioms $\{A, \neg A\}$ (inconsistent with itself) or if there is a vertex n' with emply label (either due to pruning or being a hitting set) and $H(n') \subseteq H(n)$, or if there is a vertex n' where H(n) = H(n')).

This algorithm works for single observations, like $\{a:C\}$, $\{a,b:R\}$ or $\{a:C\}$ $(A \sqcap B) \sqcup C$, but not for multiple observations, for example \mathcal{MO} {a:A,b:B}. We can obtain their explanations by finding explanations of every single observation, performing carthesian multiplication (TODO: spravne vyjadrenie? mozno konjunkcia ako kartezianskym sucinom?) over the resulting sets of explanations, and finally checking the resulting explanations for consistency with $\mathcal{K} \cup \mathcal{MO}$ and relevancy with $\mathcal{K} \cup \mathcal{O}$ for every single observation $\mathcal{O} \in \mathcal{MO}$, and the resulting observations are then checked for minimality against each other. For example, in the knowledge base K, if the explanations for $\{a:A\}$ are $\{\{b:B;a:C\},\{a:D\}\}\$ and the explanations for $\{b:B\}$ are $\{\{b:C\},\{b:D;b,a:R\}\}$, the explanation candidates before consistency and relevancy checking for observation $\{a:A,b:B\}$ are $\{\{b:B,a:C,b:C\},\{b:B;a:C;b:D;b,a:R\},\{a:D;b:C\},\{a:D;b:D;b,a:R\}\}$. since $\{b:B\} \models \{b:B\}$, the explanation candidates $\{b:B,a:C,b:C\},\{b:B;a:C;b:D;b,a:R\}$ are cut for relevancy. Let's say the remaining candidates, {a:D;b:C}, {a:D;b:D;b,a:R} are consistent with K, then they are explanations of $\mathcal{MO} = \{a : A; b : B\}$. TODO: the paradox $(a:A \sqcup B \text{ nie je to iste ako } \{a:A, a:B\})$

5.1 Our algorithm

Our algorithm is based on the H and P algorithm (TODO: ref), some main differences:

- We do not use the formalism of the HS-tree, instead we only remember the hitting set candidates (the equivalent of vertex in HS-tree) for depth d and are building a set of hitting set candidates for depth d+1
- 2. When generating antimodels, we do not generate axioms when either they or their complements are in the $\mathcal{K} \cup O$
- 3. We check for relevancy and consistency of HS candidates when they are generated, instead of at the end of the algorithm.
- 4. (TODO: Minimum inconsistent set)

${\bf Implementation}$

TODO: reasonery, logiky

```
1: function Abduction (Knowledge base K, observation O, maximum
    Depth maxD)
        Output: Set of minimum explanations S
 2:
        if \mathcal{K} \cup O is inconsistent then
 3:
            return \emptyset //observation not consistent with knowledge base
 4:
        end if
        if \mathcal{K} \cup \neg O is inconsistent then
 6:
 7:
            return {{}} //observation can be inferred from knowledge base
 8:
        end if
        C = \{\{\}\}\ //\text{hitting set candidates for this iteration (one empty set)}
 9:
        \mathcal{NC} = \emptyset //hitting set candidates for next iteration
10:
        \mathcal{S} = \emptyset
11:
        D = 1 / depth
12:
13:
        while C \neq \emptyset \land D \leq maxD do
            for each candidate c \in \mathcal{C} //TODO: malo by c tiez by tv mathcal?
14:
    do
                for each hitting set s \in \mathcal{S} do
15:
                    if s \in c then
16:
                         Continue to next candidate //expalanation wouldn't
17:
    be minimal
18:
                     end if
19:
                end for
                if \mathcal{K} \cup \{\neg O\} \cup c is inconsistent then
20:
                    if \mathcal{K} \cup c is consistent then
21:
                         \mathcal{S} = \mathcal{S} \cup c //c is a hitting set (explanation)
22:
23:
                     end if
                     Continue to next candidate
24:
                end if
25:
26:
                if D = maxD then
                     Continue to next candidate // no need to create
27:
    candidates for next while iteration
                end if
28:
                Axioms \mathcal{AX} = \operatorname{getAntiModel}(\mathcal{K}, O, c)
29:
                for each axiom ax \in \mathcal{AX} do
30:
                    if ax \in c then
31:
                         Continue to next axiom //c \cup ax \equiv c
32:
                     end if
33:
                     nc = c \cup ax
34:
                    if O \in nc then
35:
                         Continue to next axiom //explanation would be trivial
36:
                     end if
37:
                    \mathcal{NC} = \mathcal{NC} \cup nc
38:
                end for
39:
            end for
40:
            C = \mathcal{N}C
41:
            \mathcal{NC} = \emptyset
42:
        end while
43:
44: end function
```

```
1: function GETANTIMODEL( Knowledge base K, observation O, set of
     axioms \mathcal{AX})
           Output: Antimodel \mathcal{AM} of a model \mathcal{M} of \mathcal{K} \cup \{\neg O\} \cup \mathcal{AX}
 2:
           \mathcal{AM} = \emptyset
 3:
           \mathcal{M} = \text{model of } \mathcal{K} \cup \{\neg O\} \cup \mathcal{AX}
 4:
          for each individual \mathcal{I} \in \mathcal{K} \cup \mathcal{O} \cup \mathcal{AX}: do
 5:
                C_k =set of concepts \{\forall C | \mathcal{I} : C \in \mathcal{K} \} //known concepts
 6:
                C_a = \text{set of all concepts} \in \mathcal{K} / \text{all concepts}
 7:
                C_i = \text{set of concepts } \{ \forall C | \mathcal{I} : C \in \mathcal{M} \} / \text{inferred concepts} 
 8:
                for each concept C \in C_i do
 9:
                     if not C \in \mathcal{C}_k then
10:
                           \mathcal{AM} = \mathcal{AM} \cup (\mathcal{I} : C)
11:
                     end if
12:
                end for
13:
                for each concept C \in \mathcal{C}_a do
14:
                     if not C \in \mathcal{C}_i then
15:
                           \mathcal{AM} = \mathcal{AM} \cup (\mathcal{I} : C)
16:
                     end if
17:
18:
                end for
          end for
19:
          return \mathcal{AM}
21: end function
```

Results

Conclusion

Literatúra

- [1] C. Elsenbroich, O. Kutz, and U. Sattler. A case for abductive reasoning over ontologies. CEUR, 2006.
- [2] K. Halland and K. Britz. Naive abox abduction in alc using a dl tableau. In Y. Kazakov, D. Lembo, and F. Wolter, editors, *Description Logics*, volume 846 of *CEUR Workshop Proceedings*. CEUR-WS.org, 2012.
- [3] M. Krötzsch, F. Simancik, and I. Horrocks. A description logic primer. arXiv preprint arXiv:1201.4089v3, 2012.
- [4] J. Pukancová and M. Homola. Tableau-based abox abduction for description logics, 2017.
- [5] R. Reiter. A theory of diagnosis from first principles. Artificial Intelligence, 32:57–95, 1987.
- [6] R. Reiter. A theory of diagnosis from first principles. Artificial intelligence, 32(1):57–95, 1987.
- [7] S. Staab and R. E. Studer. Handbook on Ontologies. Springer, 2010.
- [8] H. Van, V. L. Frank, and P. e. Bruce. Kandbook of knowledge representation. Elsevier, 2008.

Zoznam obrázkov