In Proceedings of the Sixth International Conference on Cognitive Modeling, 350-351. Mahwah, NJ: Lawrence Earlbaum.

# **Ontological Aspects of Computing Analogies**

Helmar Gust (helmar.gust@uos.de), Kai-Uwe Kühnberger (kkuehnbe@uos.de)

Institute of Cognitive Science; University of Osnabrück, Katharinenstr. 24 49069 Osnabrück, Germany

### Ute Schmid (schmid@informatik.uni-osnabrueck.de)

Department of Mathematics and Computer Science; University of Osnabrück, Albrechtstr. 28 49069 Osnabrück, Germany

### Introduction

In AI, there is an increasing interest in examining ontologies for a variety of applications. Classical ontologies can have different forms ranging from lattice-like structures (Ganter & Wille, 1996) to less restricted semantic networks (Peters & Shrobe, 2003).

Analogical reasoning has a long tradition in cognitive science and AI. The monograph Gentner, Holyoak & Kokinov (2001) is a good summary of recent theories for analogies. An important tool for modeling analogies is anti-unification (AU), introduced in Plotkin (1970). AU is a framework to compute generalizations of source and target which in turn can be used to establish an analogical relation (Schmid, Gust, Kühnberger & Burghardt, 2003). We will extend AU to so-called heuristic-driven theory projection (HDTP) to model analogical reasoning processes.

### The Algorithm HDTP-A

We will present the algorithm HDTP-A computing generalizations together with their corresponding substitutions given a source and a target domain (Table 1). HDTP-A is based on an implementation in Gust, Kühnberger & Schmid (2003).

#### Table 1: The algorithm HDTP-A

**Input:** A set of axioms S of the source domain in a language  $L_S$ inducing a theory  $Th_S$  and a set of axioms T of the target domain in a language  $L_T$  inducing a theory  $Th_T$ . **Output:** A generalized set of axioms G in a language  $L_{S\oplus T}^+$  together with corresponding substitutions inducing a theory  $Th_G$ . T = axioms of the target domain sorted by a heuristics hS = axioms of the source domain<math>G = empty list of axioms of generalized theory  $\Theta_1 = \Theta_2 = empty$  substitution  $Th_T^{A_h} = Th_T$ FOR  $\phi \in T$  $\phi = normal\_form(\phi)$ SELECT  $\psi \in S$  $\begin{aligned} \psi &= normal_form(\psi) \\ \text{IF not } same_{structure}(\phi,\psi) \text{ REJECT} \\ \text{SELECT } (\xi,\Theta_1,\Theta_2) \in anti_{stances}(\phi,\psi,\Theta_1,\Theta_2) \end{aligned}$ WITH  $\xi$  best according to a heuristics h'IF  $h'(\xi) > a$  given threshold ADD  $\xi$  to GADD  $\xi \Theta_2$  to  $T_T^{A_h}$ REMOVE  $\psi$  from S ELSE FAIL END FOR FOR  $\psi \in S$  $\phi = transfer(\psi, \Theta_1, \Theta_2)$ IF  $T_T^{A_h} \vdash \neg \phi$  CONTINUE IF  $oracle(\phi) = FALSE$  CONTINUE ADD  $\phi$  to  $Th_{\tau}^{A_h}$ ADD generalize( $\psi, \Theta_1$ ) to G

The input is given by S (source) and T (target) inducing corresponding theories  $Th_S$  and  $Th_T$ . The output of the algorithm is a set of axioms (facts and laws) G inducing a theory  $Th_G$  generalizing source and target. The algorithm chooses an axiom from T governed by a heuristics h and searches an axiom from S to generalize both. Possible heuristics h that can be used for choosing axioms are "Select simple axioms first", or "Select axioms with a maximal number of shared terms w.r.t. already generalized terms". Additionally a heuristics h' is needed to select an anti-instance (AI) from all computed generalizations. Examples for such heuristics are "Select an AI with minimal length of substitutions" or "Select an AI with a minimal number of second-order objects". After a successful generalization the resulting axiom is added to  $Th_G$ . This processes is recursively applied to all axioms in T. Finally remaining axioms in S can be transferred to T governed by the already computed substitutions as long as consistency of the extended theory and consistency w.r.t. to oberservables (checked by experiments) is guaranteed. Examples of such transfers are discussed in Schmid, Gust, Kühnberger & Burghardt (2003).

## An Example: The Rutherford Analogy

In Table 2, representations of the source (left side) and the target (right side) of the Rutherford analogy are given. We consider *planet* and *sun* to be objects. Observable properties are *mass*, *distance*, and *force*. We assume certain laws that govern the behavior of objects in the solar system. Concerning the conceptualization of the atom (right side) we assume that objects *electron* and *nucleus* are given and observable properties are *electric charge*, *mass*, and *Coloumb force*. We presuppose that the *electron* and the *nucleus* have a *mass* and an *electric charge*. Finally we can perform an experiment (an abstract representation of the Rutherford experiment) to test whether analogical transfers yield valid results. Here are the computed generalizations:

Source Theory $S$	Target Theory T	Generalized Theory $G$
mass(s) > mass(p)	mass(n) > mass(e)	mass(Y) > mass(X)
$rev\_around(p,s)$	$rev\_around(e,n)$	$rev_around(X, Y)$
gravity(p,s,t) > 0	coloumb(e,n,t) > 0	F(X,Y,t) > 0
dist(p,s,t) > 0	dist(e, n, t) > 0	dist(X, Y, t) > 0

### Integrating Ontologies in HDTP-A

Ontologies typically order concepts hierarchically using a subsumption relation. Based on Stumme & Maedche

#### Table 2: Modeling the physics of the solar system and the atom model

```
types
     real, object, time
entities
      planet: object
                            ; sun : object
functions
     observable mass: object \times time \rightarrow real \times \{kg\}
     observable dist: object \times object \times time \rightarrow real \times {m}
     observable gravity: object \times object \times time \rightarrow real \times \{N\}
     observable centrifugal: object \times object \times time \rightarrow real \times {N}
facts
     revolves_around(planet, sun)
     mass(sun, t) > mass(planet, t)
     \forall t: time: gravity(planet,sun,t) > 0
     \forall t: \ time: \ \widetilde{dist(planet,sun,t)} > 0
laws
     \forall t: time, o_1: object, o_2: object:
        dist(o_1, o_2, t) > 0 \quad \land gravity(o_1, o_2, t) > 0
         \exists force: force(o_1, o_2, t) < 0 \land
        force(o_1, o_2, t) = centrifugal(o_1, o_2, t)
     \forall t: time, o_1: object, o_2: object:
         dist(o_1, o_2, t) > 0 \land centrifugal(o_1, o_2, t) < 0
         revolves\_around(o_1, o_2)
```

(2001), we define ontologies as follows.

**Definition 1** An ontology is a tuple  $\langle C, is_a, R, \sigma \rangle$  s.t. C is a set of concepts,  $is_a \subseteq C \times C$  is a partial order on C, R is a set of relations, and  $\sigma$  is an arity function.<sup>1</sup>

The crucial feature in this definition is the subsumption relations  $is_a$ : Concepts specialize to subconcepts and generalize to superconcepts. In Figure 1, a corresponding hierarchical structure for the solar system of the example above is depicted. The idea is to use such ontologies to block generalizations that do not have a common superconcept. If the ontology has a tree-like structure like in Figure 1, then we need to specify subtrees that allow generalizations. In Figure 1 we would like to allow a generalization of gravitation and centrifugal and (under certain circumstances) the generalization of force and distance.



gravitation centrifugal

Figure 1: A possible ontology for for the model  $\mathfrak{M}_1$ .

**Definition 2** Assume an ontology  $O = \langle C, is_a, R, \sigma \rangle$ and a set  $C_{gen} \subseteq C$  are given.<sup>2</sup> The generalizable expressions O' relative to a function Sort mapping terms to sorts are defined as follows:

If  $t_1$  and  $t_2$  are terms, then  $\langle t_1, t_2 \rangle \in O'$  iff there exists  $c \in C_{gen}$  with  $Sort(t_1)$  is\_a c and  $Sort(t_2)$  is\_a c.

If  $\phi$  and  $\psi$  are complex, then  $\langle \phi, \psi \rangle \in O'$  iff all corresponding subterms are generalizable.

Using the definition of generalizable expressions the modified FOR-loop of the algorithm HDTP-A is depicted in Table 3 (given T and S, and an ontology O).

<sup>1</sup>In this paper, R and  $\sigma$  are not relevant.

<sup>2</sup>The intended interpretation of  $C_{gen}$  is a set of leaves of an upper structure, in our example the set {*time, object, date*}.

```
types
     real, object, time
entities
      electron: object
                              ; nucleus : object
functions
     observable mass: object × time \rightarrow real × {kg}
observable dist: object × object × time \rightarrow real × {m}
      observable \ electric\_charge: \ object \rightarrow \ real \times \ \{eV\}
     observable coloumb: object \times object \times time \rightarrow real \times \{N\}
facts
     mass(nucleus, t) > mass(electron, t)
      electric_charge(electron) < 0
     electric\_charge(nucleus) > 0
     \forall t: time: coloumb(electron.nucleus.t) > 0
experiment
      \forall t: time: dist(electron, nucleus, t) > 0
```

Table 3: The modified algorithm HDTP-A

```
 \begin{array}{l} \text{FOR } \phi \in T \\ \phi = normal\_form(\phi) \\ \text{SELECT } \psi \in S \\ \psi = normal\_form(\psi) \\ \text{IF not } same\_structure(\phi,\psi) \text{ REJECT} \\ \text{IF not } \langle \phi,\psi\rangle \in O' \text{ REJECT} \\ \text{SELECT } (\xi,\Theta_1,\Theta_2) \in anti\_instances(\phi,\psi,\Theta_1,\Theta_2) \\ \text{WITH } \xi \text{ best according to a heuristics } h' \\ \text{IF } h'(\xi) > a \text{ given threshold} \\ \text{ADD } \xi \text{ to } G \\ \text{ADD } \xi \Theta_2 \text{ to } T_A^{-h} \\ \text{REMOVE } \psi \text{ from } S \\ \text{ELSE FAIL} \\ \text{END FOR} \end{array}
```

A test relative to a given ontology O is integrated in the algorithm HDTP-A in order to reduce the search space for possible generalizations. The corresponding ontological commitments are clearly domain dependent.

#### References

- Ganter, B. & Wille, R. (1996). Formale Begriffsanalyse. Mathematische Grundlagen. Berlin, Heidelberg: Springer.
- Gentner, D., Holyoak, K. & Kokinov, B. (2001). The Analogical Mind. Perspectives from Cognitive Science. Cambridge, MA.
- Gust, Н., K.-U. Schmid, U. Kühnberger, & of (2003).Anti-unification axiomatic svshttp://www.cogsci.uniavailable tems. online: osnabrueck.de/~helmar/analogy1.ps/
- Peters, S. & Shrobe, H. (2003). Using Semantic Networks for Knowledge Representation in an Intelligent Environment. First IEEE International Conference on Pervasive Computing and Communications, Forth Worth, Texas, pp. 323-337.
- Plotkin, G. (1970). A note on inductive generalization. Machine Intelligence, 5, pp. 153-163.
- Schmid, U., Gust, H., Kühnberger, K.-U. & Burghardt, J. (2003). An Algebraic Framework for Solving Proportional and Predictive Analogies. In F. Schmalhofer, et.al. (Eds.), *Proceedings of the European Conference on Cognitive Sci*ence (pp. 295-300), Lawrence Erlbaum.
- Stumme, G. & Maedche, A. (2001). FCA-MERGE: Bottom-Up Merging of Ontologies. Proceedings of the 7th Internatioanl Joint Conference on Artificial Intelligence (pp. 225-230), Seattle, WA.