

# Provenance for Explaining Taxonomy Alignments

Mingmin Chen<sup>1</sup>, Shizhuo Yu<sup>1</sup>, Parisa Kianmajd<sup>1</sup>, Nico Franz<sup>2</sup>,  
Shawn Bowers<sup>3</sup>, and Bertram Ludäscher<sup>1</sup>

<sup>1</sup> Dept. of Computer Science, UC Davis,

{michen, szyu, pkianmajd, ludaesch}@ucdavis.edu

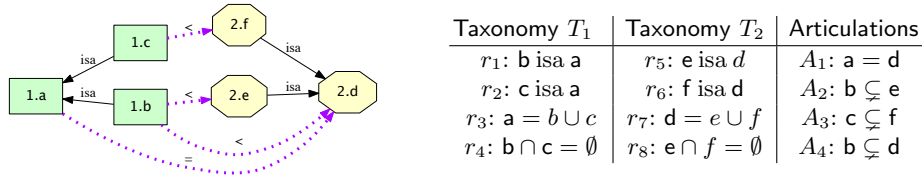
<sup>2</sup> School of Life Sciences, Arizona State University, nico.franz@asu.edu

<sup>3</sup> Dept. of Computer Science, Gonzaga University, bowers@gonzaga.edu

Derivations and proofs are a form of provenance in automated deduction that can assist users in understanding how reasoners derive logical consequences from premises. However, system-generated proofs are often overly complex or detailed, and making sense of them is non-trivial. Conversely, without any form of provenance, it is just as hard to know why a certain fact was derived.

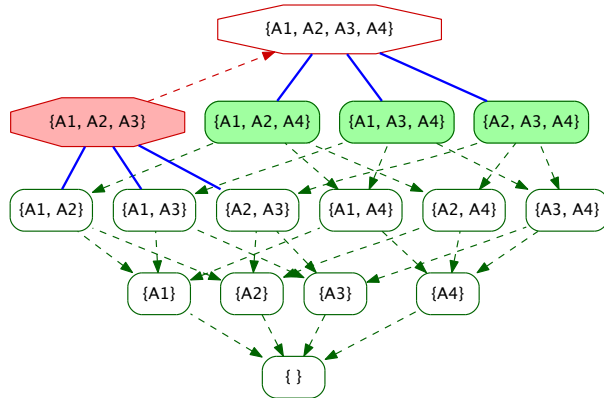
We study provenance in the application of EULER/X [1], a logic-based toolkit for aligning multiple biological taxonomies. We propose a combination of approaches to explain both, logical inconsistencies in the input alignment, and the derivation of new facts in the output taxonomies.

**Taxonomy Alignment.** Given taxonomies  $T_1, T_2$  and a set of *articulations*  $A$ , all modeled as monadic, first-order constraints, the *taxonomy alignment problem* is to find “merged” taxonomies that satisfy  $\Phi = T_1 \cup T_2 \cup A$ . An alignment can be *inconsistent* ( $\Phi$  is unsatisfiable), *unique* ( $\Phi$  has exactly one minimal model), or *ambiguous* ( $\Phi$  has more than one minimal model). For example, let  $T_1$  be given by *isa* (subset) constraints  $b \subseteq a$ ,  $c \subseteq a$ , *coverage* constraint  $a = b \cup c$ , and *sibling disjointness*  $b \cap c = \emptyset$ . Similarly,  $T_2$  is given by *isa* constraints  $e \subseteq d$ ,  $f \subseteq d$ , *coverage*  $d = e \cup f$ , and *sibling disjointness*  $e \cap f = \emptyset$ .



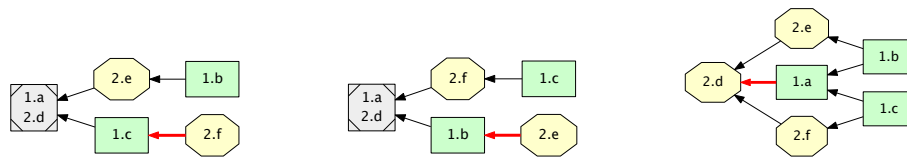
**Fig. 1.** Alignment Problem: Taxonomies  $T_1$  (given by set constraints  $r_1, \dots, r_4$ ) and  $T_2$  (constraints  $r_5, \dots, r_8$ ) are related via articulations  $A$  (constraints  $A_1, \dots, A_4$ ).

An expert aligns  $T_1$  and  $T_2$  using *articulations*  $a = d$ ,  $b \subseteq e$ ,  $c \subseteq f$ , and  $b \subseteq d$ ; see Figure 1. We would like to “apply” all of these relations between the two taxonomies, and output a merged taxonomy.



**Fig. 2.** Diagnosis for  $A = \{A_1, \dots, A_4\}$ : solid red octagons and solid green boxes denote MIS and MCS, respectively. The (in)consistency of all other combinations are implied.

**Inconsistency Explanation.** Usually  $T_1$  and  $T_2$  are considered immutable or correct by definition, whereas  $A$  might contain modeling errors. EULER/X applied to Fig. 1 finds that the constraints are unsatisfiable, and performs a model-based diagnosis. The result lattice (Fig. 2) highlights *minimal inconsistent subsets* (MIS) and *maximal consistent subsets* (MCS). The MIS  $\{A_1, A_2, A_3\}$  indicates which articulations are inconsistent with  $T_1, T_2$ . To further explore the inconsistency, the system-derived MCS can be employed: Fig. 3 shows the merged taxonomies (a.k.a. “possible worlds”) obtained from the MCS. Here, each MCS corresponds to one possible world.<sup>4</sup>

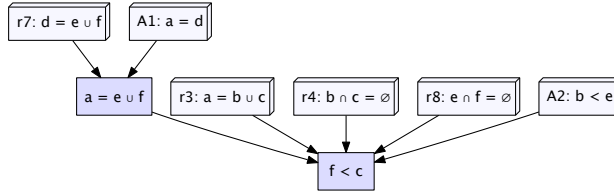


**Fig. 3.** Merged taxonomies (*possible worlds*) for MCS  $\{A_1, A_2, A_4\}$ ,  $\{A_1, A_3, A_4\}$ , and  $\{A_2, A_3, A_4\}$ . Grey boxes are fused concepts; bold, red edges represent inferred relations.

Using expert knowledge or further constraints<sup>5</sup> a preferred merge result can be selected to further analyze and then repair the inconsistency. Here, suppose the user chose the first maximal consistent subset  $\{A_1, A_2, A_4\}$ . It follows from  $A_1, A_2$  and the input taxonomies  $T_1, T_2$  that  $f \subsetneq c$ . However,  $A_3$  is  $c \subsetneq f$  yielding a contradiction. Now the problem is to explain why  $f \subsetneq c$  is inferred.

<sup>4</sup> In general, a MCS can yield many possible worlds. Such ambiguities arise when the alignment input is underspecified.

<sup>5</sup> E.g., the output for MCS  $\{A_2, A_3, A_4\}$  might be less desirable since it is not a tree.



**Fig. 4.** Provenance of  $f \subsetneq c$  (depicted as  $f < c$ ). Lightly colored 3D-boxes are input facts (taxonomies and input alignment). Inferred relations are shown as darker boxes.

**Derivation Explanation.** To understand how  $f \subsetneq c$  is inferred, we may need to inspect its logical derivation or an abstraction of it. We obtain this provenance in EULER/X by keeping track of the rules  $r_1, \dots, r_8$  and input alignments  $A_1, \dots, A_4$  used by the reasoner. Fig. 4 depicts the resulting provenance overview.

**Related Work.** Data provenance is an actively researched area and is closely related to proofs and derivations in logical reasoning. Our inconsistency explanation is based on Reiter’s model-based diagnosis [6], which has been studied extensively and applied to many areas, e.g., type error debugging, circuit diagnosis, OWL debugging, etc. We have adapted the HST algorithm in [4] to compute all MIS and MCS for inconsistency explanation. The problem was shown to be TRANS-ENUM-complete by Eiter and Gottlob [2]. Inspired by the ideas of a provenance semirings [3] and Datalog debugging [5], our approach explains the derivation of the inferred relations.

*Acknowledgments.* Supported in part by NSF IIS-1118088 and DBI-1147273.

## References

1. M. Chen, S. Yu, N. Franz, S. Bowers, and B. Ludäscher. Euler/X: A toolkit for logic-based taxonomy integration. In *22nd Intl. Workshop on Functional and (Constraint) Logic Programming (WFLP)*, Kiel, Germany, 2013.
2. T. Eiter and G. Gottlob. Hypergraph transversal computation and related problems in logic and AI. In *European Conference on Logics in Artificial Intelligence (JELIA)*. LNCS 2424, Springer, 2002.
3. T. Green, G. Karvounarakis, and V. Tannen. Provenance semirings. In *ACM Symposium on Principles of Database Systems (PODS)*, pages 31–40, 2007.
4. M. Horridge, B. Parsia, and U. Sattler. Explaining inconsistencies in OWL ontologies. In *Scalable Uncertainty Management*, LNCS 5785, Springer, 2009.
5. S. Köhler, B. Ludäscher, and Y. Smaragdakis. Declarative datalog debugging for mere mortals. In *Datalog in Academia and Industry*, LNCS 7494, Springer, 2012.
6. R. Reiter. A theory of diagnosis from first principles. *Artificial intelligence*, 32(1):57–95, 1987.