Experimental Evaluation of General Concept Inclusions Learned from Textual Data.

Hybris B1: Automatic Generation of Description Logic-based Biomedical Ontologies

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TU Dresden

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- Learn *all* GCIs that are valid in the text corpus
- Find a way to evaluate them

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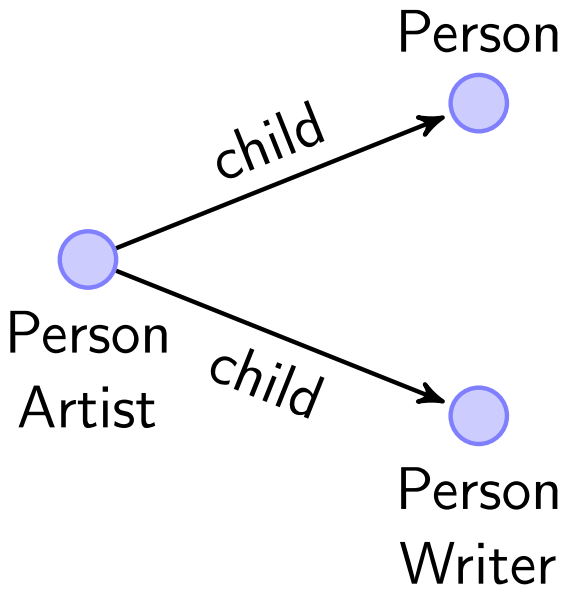

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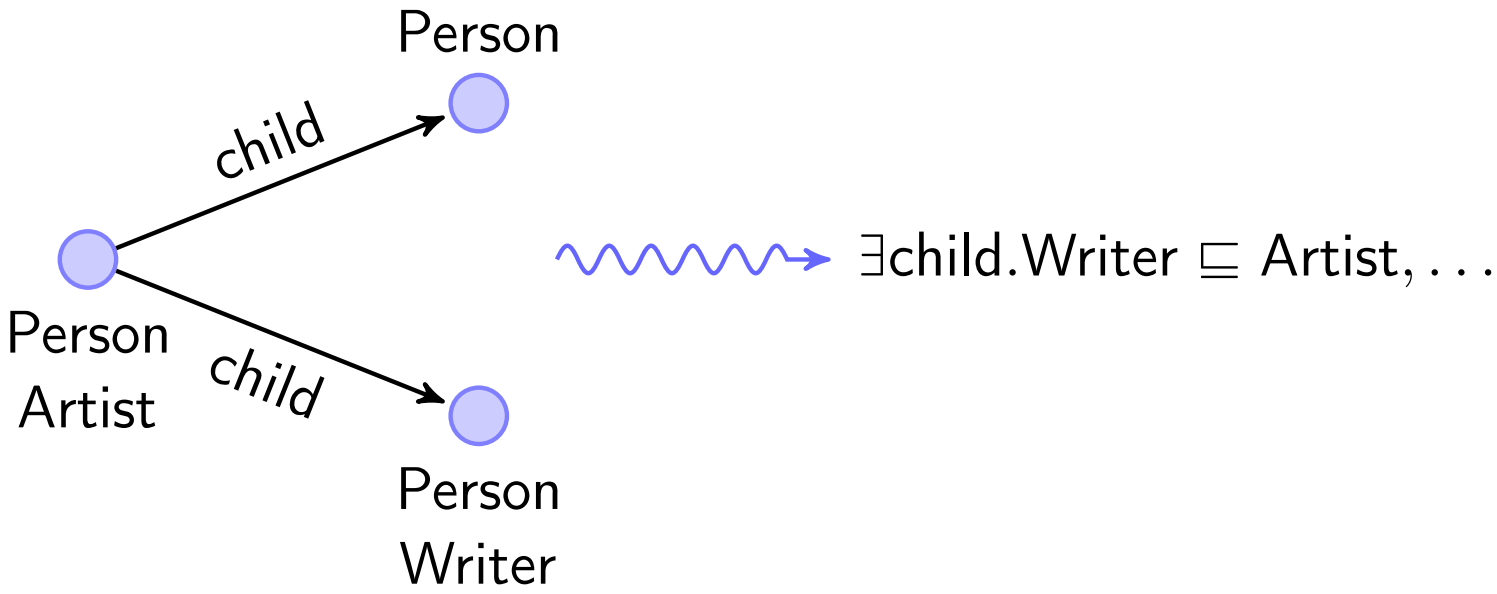

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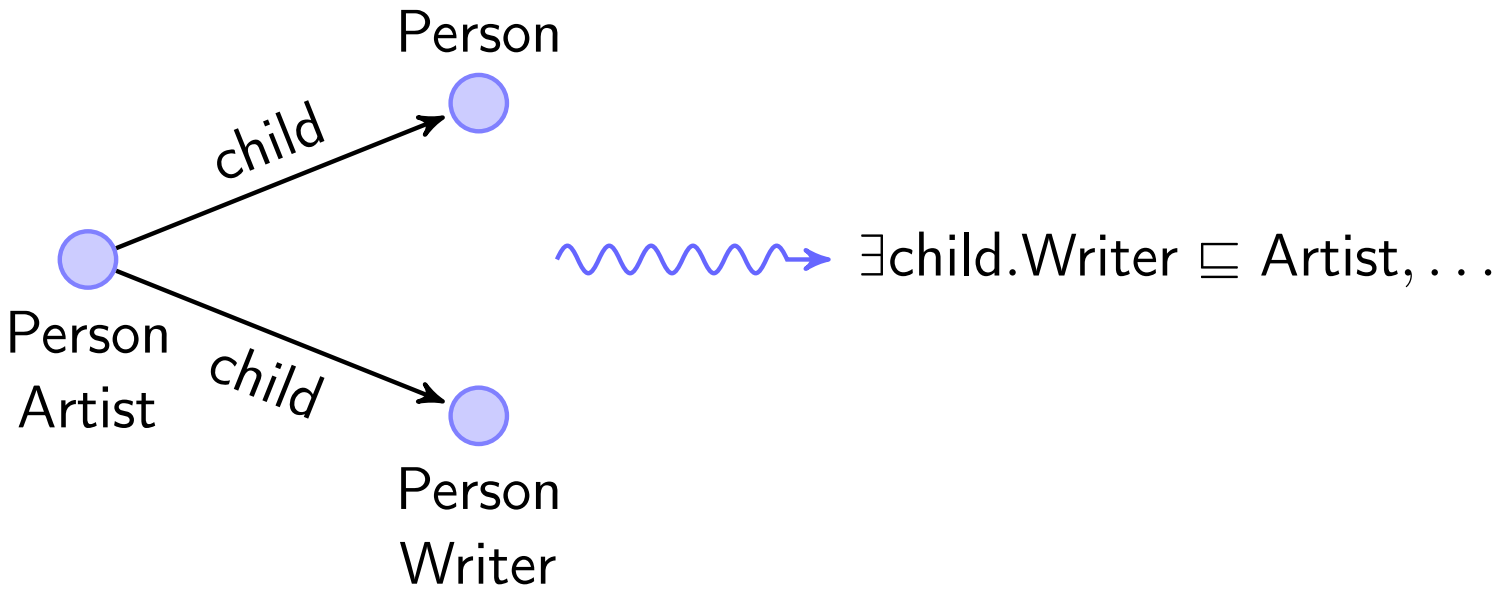

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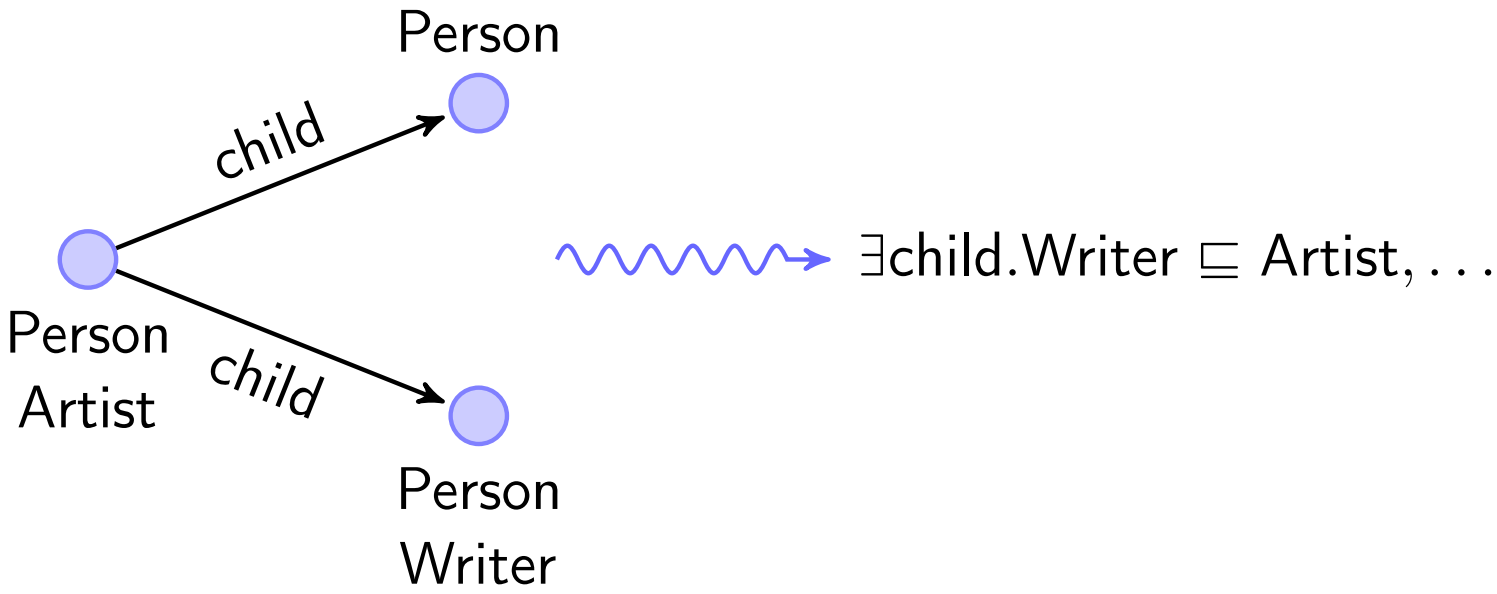

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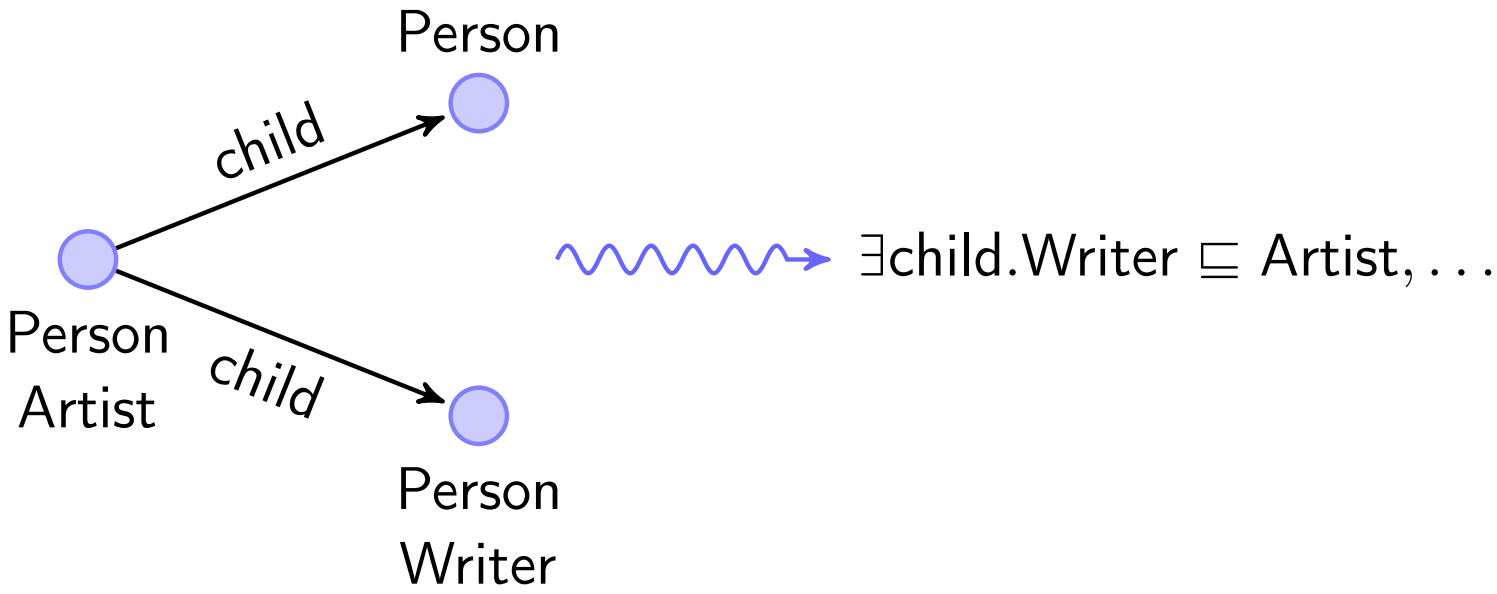

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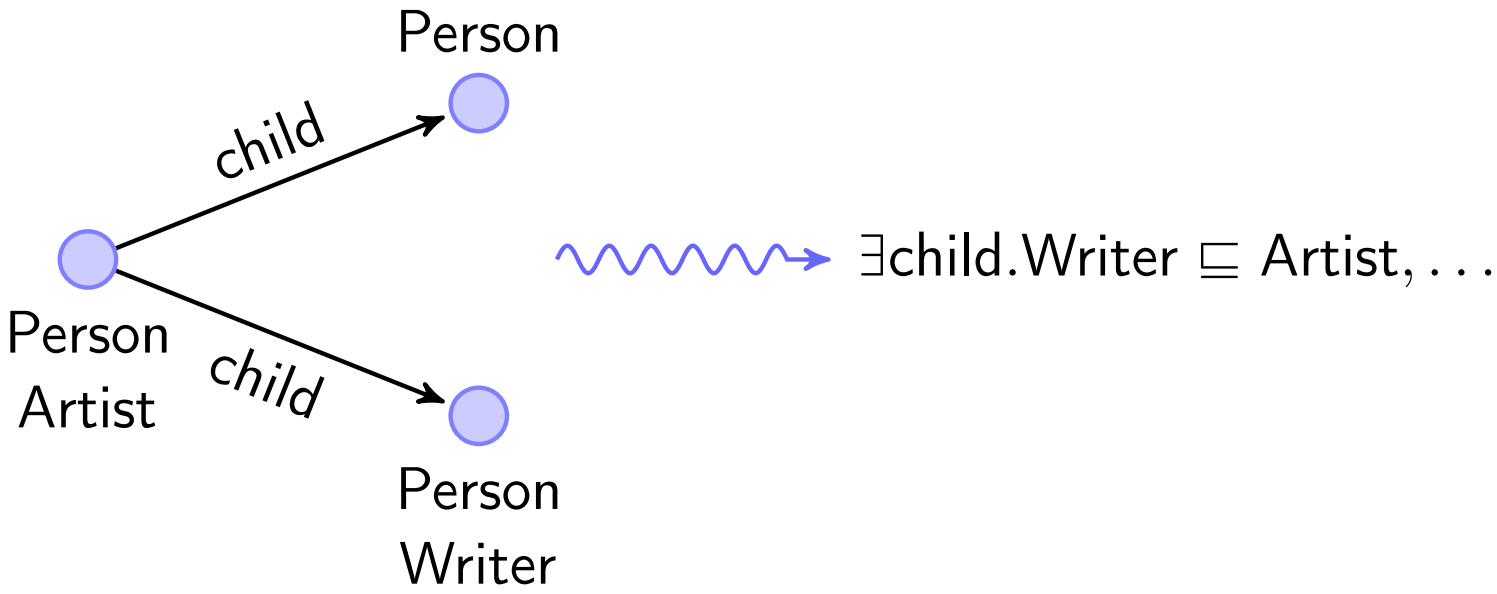

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- Implementations available (prototypes)

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- Learning uses closed-world semantics

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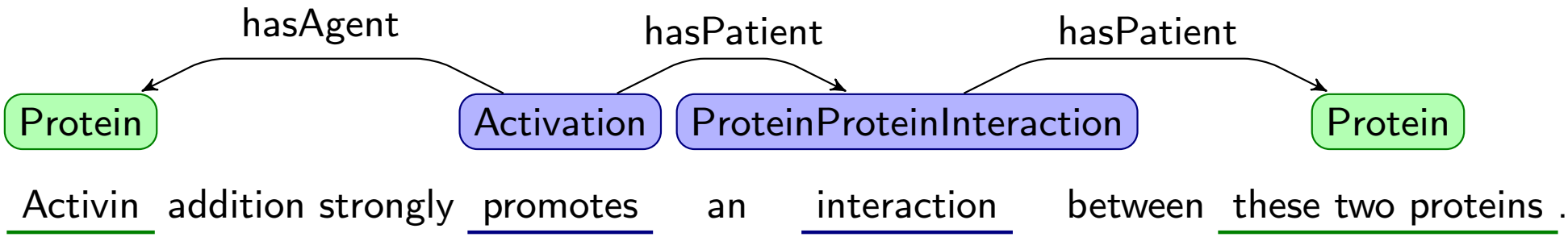

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- In the GRO, CellComponent is a super-class of Nucleus
- So, the annotation is *incomplete*

Conclusion

- unsatisfiable classes can arise through the *closed-world* interpretation of the *open-world* data-set.

Unsatisfiable Classes

Question: Where do they come from?

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- unsatisfiable classes can arise through the *closed-world* interpretation of the *open-world* data-set.
- *all* disjointness axioms containing only concept-names are caused by this

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$$\exists \text{locatedIn}.\text{Cell} \sqcap \exists \text{locatedIn}.\text{Nucleus} \sqsubseteq \text{Protein}$$

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Remove concept-names not occurring in the data-set before evaluation?

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Consider also GCIs which are correct in a "large number" of cases.

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- Devise evaluation that is "independent" from the data-set?