Additional Information on Datasets and Concept Learning

No Author Given

No Institute Given

Family Ontology We used an slightly extended version of the Family ontology from SML-Bench [2]. We added a super role `hasPartner` of `married` to the original Family ontology because the original ontology had none, and we wanted it to include a role hierarchy, so that we had an actual example of $\mathscr{ELH}$ and not just $\mathscr{EL}$. To obtain (complex) concepts for the generation of counterfactuals, for each atomic concept present in the ontology, we did the following: First, we removed the atomic concept from the ontology. Then, we let the DL concept learner [1] with ELTL learn a concept using 10 randomly chosen individuals that formerly were instances of the atomic concept as positive examples, and 10 random others as negative examples. Thereafter, we randomly selected an individual which is an instance of that concept and applied our counterfactual algorithm. We manually inspected the learned concepts and used the correct concepts for the survey (e.g., concept `Father` leads to $\texttt{Male} \sqcap \exists \texttt{hasChild}.\top$). For consistency, we also queried for the concepts for `Brother` and `Grandmother` as the corresponding concepts to `Sister` and `Grandfather` in the survey, even if ELTL did not correctly recognize the concept. This way, we ended up with `Mother`/`Father`, `Sister`/`Brother` and `Grandmother`/`Grandfather` for the survey.

Animals Ontology We used modified version of the Animals ontology from SML-Bench [2]. We added two super roles to the Animals ontology, i.e., `residence` and `home`, for the same reasons as above. Furthermore, we restructured the ontology to fit $\mathscr{ELH}$ semantics. The atomic concepts of species were removed and their roles added to the individual animals. This way we could train ELTL [1] to learn a concept for each species, using the instance belonging to that species as positive example, and all other instances of animals as negative examples. Our algorithm was applied afterwards. From the generated concepts, we ignored those that lead to only one possible explanation, the concept for "boy" becuse it was identical to "girl", and those that included the existential restricion $\exists \textit{hasCovering}.\top$, because it produces no reasonable counterfactual sentence that participants could easily understand. Of the others, we chose 6 randomly to use these and their counterfactual candidates for the survey.

References

1. Bühmann, L., Lehmann, J., Westphal, P.: Dl-learner - A framework for inductive learning on the semantic web. J. Web Semant. **39**, 15–24 (2016)
2. Westphal, P., Bühmann, L., Bin, S., Jabeen, H., Lehmann, J.: Sml-bench - A benchmarking framework for structured machine learning. Semantic Web **10**(2), 231–245 (2019)