Abstraction in First-Order Probabilistic Inference

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First-Order Probabilistic Inference

Markov Logic Network

- $0.7 \ \forall x \forall y \forall z \ Friends(x, y) \land Friends(y, z) \implies Friends(x, z)$
- 2.3 $\forall x \neg \exists y \text{ Friends}(x, y) \implies \text{Smokes}(x)$
- 1.5 $\forall x \text{ Smokes}(x) \implies \text{Cancer}(x)$
- 1.1 $\forall x \forall y \text{ Friends}(x, y) \implies (\text{Smokes}(x) \iff \text{Smokes}(y))$

First-order probabilistic models are representations combining elements of first-order logic with probabilities. In a Markov logic network [2], each statement is accompanied by a weight which can be used to calculate the probability of an event such as Cancer (Cathy) or Friends (Ross, Joey). These models have a wide range of applications, ranging from cancer research to predicting criminal behaviour. Combining NP-complete and #P-complete problems, inference is a challenging problem.

Methodology abstract model inference approximation abstract query error bound is within

Abstraction can be used to improve inference speed by simplifying the model beforehand. We can find an abstract representation of a model specific to each query, and perform inference on the abstraction. The abstraction may be **exact** and produce the same answer as the original model, or it may produce a bounded approximation. An abstraction can be created by applying a combination of **atomic transformations** in a **greedy** manner.

Abstraction

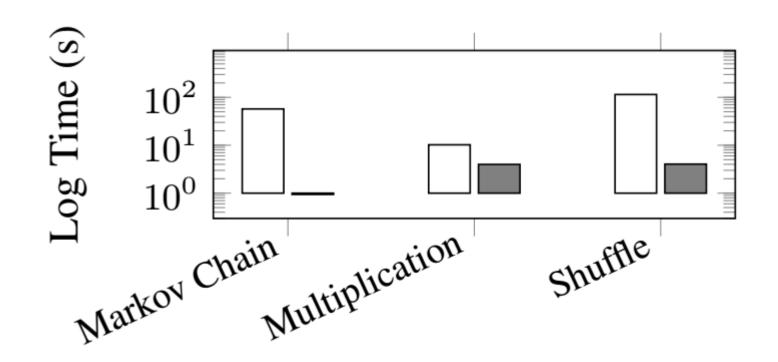


Fig. 1: Inference running time before and after abstraction for several example tasks in a probabilistic programming language Psi. Although **abstraction** for rich probabilistic models is a new and emerging field, recent work by Holtzen et al. [1] shows **promising results** in applying **predicate abstraction** on probabilistic programs. **Our goal** is to consider a wide range of abstractions, understand their properties, and determine how to combine them in a successful manner.

Impact

This work is likely to result in significant improvements in **inference speed**, increase the **explainability** of models learned from data, and make the models more **scalable**.

References

- [1] S. Holtzen, G. V. den Broeck, and T. D. Millstein. "Sound Abstraction and Decomposition of Probabilistic Programs". In: *Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholmsmässan, Stockholm, Sweden, July 10-15, 2018.* Ed. by J. G. Dy and A. Krause. Vol. 80. JMLR Workshop and Conference Proceedings. JMLR.org, 2018, pp. 2004–2013.
- [2] M. Richardson and P. M. Domingos. "Markov logic networks". In: *Machine Learning* 62.1-2 (2006), pp. 107–136. DOI: 10.1007/s10994-006-5833-1.