TLP **15** (2): 145–146, 2015. © Cambridge University Press 2014
doi:10.1017/S1471068413000665 First published online 23 May 2014

Introduction to the special issue on probability, logic and learning

JAMES CUSSENS

Department of Computer Science and York Centre for Complex Systems Analysis
University of York, York YO10 5GE, UK
(*e-mail:* james.cussens@york.ac.uk)

LUC DE RAEDT and ANGELIKA KIMMIG

Department of Computer Science, KU Leuven, Celestijnenlaan 200a, 3001 Heverlee, Belgium
(*e-mail:* {luc.deraedt, angelika.kimmig}@cs.kuleuven.be)

TAISUKE SATO

Department of Computer Science, Tokyo Institute of Technology
Ookayama 2-12-1, Meguro-ku, Tokyo, Japan
(*e-mail:* sato@mi.cs.titech.ac.jp)

Recently, the combination of probability, logic and learning has received considerable attention in the artificial intelligence and machine learning communities; see e.g. Getoor and Taskar (2007); De Raedt *et al.* (2008). Computational logic often plays a major role in these developments since it forms the theoretical backbone for much of the work in probabilistic programming and logical and relational learning. Contemporary work in this area is often application- and experiment-driven, but is also concerned with the theoretical foundations of formalisms and inference procedures and with advanced implementation technology that scales well.

Many probabilistic logic programming languages, including PRISM (Sato and Kameya 2001), Logic Programs with Annotated Disjunctions (LPADs) (Vennekens *et al.* 2004), ProbLog (De Raedt *et al.* 2007), and ICL (Poole 2008), are probabilistic extensions of Prolog based on Sato's distribution semantics (Sato 1995). Specifically, such languages introduce probabilistic truth values into Prolog, such as probabilistic facts, which are true (or false) with a certain probability, or probabilistic choices, that is, groups of facts only one of which is true at any point. Key computational tasks in such languages include *probabilistic inference*, that is, calculating the probability that a query follows from such a probabilistic program, *parameter learning*, that is, determining the best parameters (probabilities of the probabilistic elements) given by observed data, and *structure learning*, that is, determining the logical structure of the program (as well as its parameters) from data. This special issue presents recent developments on both parameter and structure learning, as well as an application and results on the complexity of inference.

In their paper "Viterbi training in PRISM," Sato and Kubota introduce Viterbi training for PRISM, which provides an efficient means to learn parameters of PRISM programs with hidden variables, that is, probabilistic choices whose values are not provided in the training data.

https://doi.org/10.1017/S1471068413000665 Published online by Cambridge University Press

Bellodi and Riguzzi's paper "Structure learning of probabilistic logic programs by searching the clause space" presents a new algorithm to learn the structure of LPADs, which improves on its predecessor by first determining a promising subset of clauses, and then selecting the final set of clauses among those.

In their paper "A probabilistic logic programming event calculus," Skarlatidis *et al*. apply probabilistic logic programming to human activity recognition in video, adapting a dialect of the Event Calculus to ProbLog to obtain a system that recognizes long-term activities as temporal combinations of short-term activities, taking into account the uncertainty naturally occurring in this task.

While many existing inference algorithms for probabilistic logic languages rely on some form of *grounding* to a propositional level, *lifted inference* techniques (e.g., Kersting 2012) avoid the blowup associated with such approaches by reasoning directly on the first-order level, thus exploiting symmetry and repetition, similar to resolution in the first-order logic. In his paper "Lower complexity bounds for lifted inference," Jaeger provides lower bounds on the complexity of inference in another popular class of probabilistic logic models, namely undirected probabilistic models based on quantifier- and function-free fragments of the first-order logic, such as Markov Logic Networks (Richardson and Domingos 2006).

References

De Raedt, L., Frasconi, P., Kersting, K. and Muggleton, S., Eds. 2008. *Probabilistic Inductive Logic Programming – Theory and Applications*. Lecture Notes in Computer Science, vol. 4911. Springer, Berlin, Germany.

De Raedt, L., Kimmig, A. and Toivonen, H. 2007. ProbLog: A probabilistic Prolog and its application in link discovery. In *Proceedings of the 20th International Joint Conference on Artificial Intelligence (IJCAI-07)*, Hyderabad, India, M. M. Veloso, Ed. 2462–2467.

Getoor, L. and Taskar, B., Eds. 2007. *Statistical Relational Learning*. MIT Press, Cambridge, MA.

Kersting, K. 2012. Lifted probabilistic inference. In *Proceedings of the 20th European Conference on Artificial Intelligence (ECAI-12)*, L. De Raedt, C. Bessière, D. Dubois, P. Doherty, P. Frasconi, F. Heintz and P. J. F. Lucas, Eds. Frontiers in Artificial Intelligence and Applications, vol. 242. IOS Press, Amsterdam, the Netherlands, 33–38.

Poole, D. 2008. The independent choice logic and beyond. Lecture Notes in Computer Science, Vol. 4911. Springer, New York, NY. (See De Raedt 2008), 222–243.

Richardson, M. and Domingos, P. 2006. Markov logic networks. *Machine Learning 62,* 1–2, 107–136.

Sato, T. 1995. A statistical learning method for logic programs with distribution semantics. In *Proceedings of the 12th International Conference on Logic Programming (ICLP-95)*, L. Sterling, Ed. MIT Press, Cambridge, MA, 715–729.

Sato, T. and Kameya, Y. 2001. Parameter learning of logic programs for symbolic-statistical modeling. *Journal of Artificial Intelligence Research 15*, 391–454.

Vennekens, J., Verbaeten, S. and Bruynooghe, M. 2004. Logic programs with annotated disjunctions. In *Proceedings of the 20th International Conference on Logic Programming (ICLP-04)*, B. Demoen and V. Lifschitz, Eds. Lecture Notes in Computer Science, vol. 3132. Springer, New York, NY, 431–445.

https://doi.org/10.1017/S1471068413000665 Published online by Cambridge University Press