Learning to reason and understand the world’s knowledge is a fundamental problem in AI. While it is always hypothesized that both the symbolic and statistical approaches are necessary for building intelligent systems, in practice, bridging the two in a combined framework might bring intractability—most probabilistic first-order logics are simply not efficient enough for real-world sized tasks.

In this thesis, we propose a new, scalable probabilistic logic called ProPPR to combine the best of the symbolic and statistical worlds. ProPPR has the rich semantic representation of Prolog, but we associate a feature vector to each clause, such that each clause has a weight vector that can be learned from the training data. Instead of searching over the entire graph for solutions, ProPPR uses a provably-correct approximate personalized PageRank to construct a subgraph for local grounding: the inference time is now independent of the size of the KB. We show that ProPPR can be viewed as a recursive extension to the path ranking algorithm (PRA), and outperforms PRA in the inference task with one million facts from NELL.

This thesis also provides a scalable solution to the structure learning problem in statistical relational learning. We propose an iterative structural gradient approach to exploit a second-order abductive theory, whose parameter corresponds to plausible first-order inference rules. Furthermore, to learn a set of compact theory, we show that it is possible to apply a group Lasso based structured sparsity as a soft version of predicate invention to this task. Finally, we demonstrate that ProPPR can be used as a generic framework to combine the knowledge and text based methods, where we jointly learn (1) how to extract new KB facts from the relation mentions, and (2) a set of logical rules that allow one to infer new KB facts.