Using Deep Learning Platforms to Perform Inference over Knowledge Bases

Abstract: Diffent subcommunities of artificial intelligence have focused on different toolkits, containing different computational methods and analytic techniques. The knowledge representation (KR) and logic programming (LP) communities have focused on non-probabilistic first-order inference, and has relied heavily on computational complexity as guidance for design of inference systems; the probabilistic logic (PL) community has focused on probabilistic robust inference, but has large focused on inference methods that are computationally expensive and hence do not scale to large knowledge bases; the automatic knowledge-base construction (AKBC) community has focused on constructing and using very large amounts of simple structured information; and the machine learning (ML) community has focused on learning from data how to perform simple probabilistic operations like classification. Recently progress in ML has been greatly accelerated by high-performance, easily programmable tools for defining and optimizing deep neural-network architectures.

In this talk, I will summarize the most recent results in my attempts to bridge all of these areas. Specifically, I will describe a system that learns from data how to perform non-trivial probabilistic first-order inference tasks, efficiently, in a manner that scales with large KBs. The system I will describe, TensorLog, is a carefully restricted probabilistic first-order logic in which inference can be compiled to differentiable functions in a neural network infrastructure, such as Tensorflow. This enables one to use high-performance deep learning frameworks to learn parameters of a probabilistic logic. TensorLog has been used for several diverse tasks, including semi-supervised learning for network data (using logic constraints on classifiers), question-answering against a KB, and relational learning.