Beyond Prediction: Directions for Probabilistic and Relational Learning

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Abstract. Research over the past several decades in learning logical and probabilistic models has greatly increased the range of phenomena that machine learning can address. Recent work has extended these boundaries even further by unifying these two powerful learning frameworks. However, new frontiers await. Current techniques are capable of learning only a subset of the knowledge needed by practitioners in important domains, and further unification of probabilistic and logical learning offers a unique ability to produce the full range of knowledge needed in a wide range of applications.

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1 Introduction

The past decade has produced substantial progress in unifying methods for learning logical and probabilistic models. We now have a large array of representations, algorithms, performance characterizations, and applications that bring together these two keys to effective learning and reasoning. Much of this work has sought to preserve key attributes of existing learning algorithms (e.g., efficiency) while extending the expressiveness of the representations that can be learned. However, combining probabilistic and logical techniques may open up entirely new capabilities that should not be ignored.

Specifically, these recent advances in machine learning for relational data sets have revealed a surprising new opportunity to learn causal models of complex systems. The opportunity is a potentially deep and unexploited technical interaction between two previously unconnected areas: (1) work in statistical relational learning; and (2) work on quasi-experimental design in the social sciences. Specifically, the type of new data representations conceived and exploited recently by researchers in statistical relational learning (SRL) may provide all the information needed to automatically apply powerful statistical techniques from the social sciences known as quasi-experimental design (QED). QEDs allow a researcher to exploit unique characteristics of sub-populations of data to make strong inferences about cause-and-effect
dependencies that would otherwise be undetectable. Such *causal dependencies* infer whether manipulating one variable will affect the value of another variable, and they make such inferences based on non-experimental data.

To date, QEDs have been painstakingly applied by social scientists in an entirely manual way. However, data representations from SRL that record relations (organizational, temporal, spatial, and others) could facilitate automatic application of QEDs. Constructing methods that automatically identify sub-populations of data that meet the requirements of specific QEDs would enable strong and automatic causal inferences from non-experimental data. This fusion of work in SRL and QED would lead to: (1) large increases in the percentage of causal dependencies that can be accurately inferred from non-experimental data; (2) substantial reductions in the amount of data needed to discover causal dependencies that can already be inferred; and (3) reductions in the computational complexity of causal learning algorithms.

If exploited, this capability could substantially improve the ability of researchers to construct causal models of large and complicated systems (e.g., social systems, organizations, and computer systems). Such models would be a significant improvement over existing models learned by statistical and machine learning techniques, the vast majority of which are non-causal (and thus do not allow analysts to correctly infer the effects of potential actions) or only weakly causal (because many of the potential causal dependencies cannot be correctly inferred).

## 2 Why Causal Models Are Useful

Nearly all algorithms for machine learning analyze data to identify statistical associations among variables. That is, they identify variables of some entity (e.g., a patient's occupation, recent physical contacts, and symptoms) that are statistically associated with other variables (e.g., a disease). Such associations are useful for making predictions about the values of unobserved variables based on the values of variables that can be observed. For example, a doctor could predict whether a patient has a particular disease (an unobserved variable) based on a set of observed symptoms.

Such associational models can be useful in many situations. For example, associational models constructed by machine learning algorithms now sit at the heart of most state-of-the-art systems for machine translation, speech understanding, computer vision, information extraction, and information retrieval. In all of these cases, associations among variables alone are sufficient to meet the goals of the deployed system.

However, machine learning algorithms are often deployed in the hope that they will support decisions about which actions, or *interventions*, to make in a given situation. In the case of medical diagnosis, most medical professionals do not simply want to diagnose disease, but to prevent, treat, or mitigate the effects of the disease as well. They want to know what effect a particular intervention (e.g., implementation of a public health measure or widespread administration of a drug) will have on the health of a population. In such situations, practitioners want models that help them to