Causal inference: from prediction to decision making

Many of the most important questions in science and in our personal lives are about the outcomes of doing something. Will asking people to pay upfront at the doctors reduce long term health expenditure? If we developed a drug to suppress particular genes, could we cure MS and would delaying teen-aged pregnancies improve the outcome for their kids.

These are hard questions because they require more than identifying a pattern in data. Correlation is not causation. Causal inference has proven so difficult using standard methods (such as instrumental variables and propensity scoring) that there is barely any consensus on even enduring questions like the returns to education or the long-term consequences of early life events – like teenage pregnancy, where the variables involved are susceptible to human intuition and understanding.

We now live in a world of data. Hours of our lives are spent online, where every click can be recorded, tiny computers and sensors are cheap enough to incorporate into everything and the US Institute of Health is considering if all infants should be genetically sequenced at birth. Such data gives us a window into many aspects of our lives at an unprecedented scale and detail but it is messy, complicated and often generated as a by product of some other purpose. It does not come from the controlled world of a randomised experiment. Traditional techniques that assume linearity or substantial prior knowledge of causal structure are poorly suited to data sets that may be high dimensional, have non-linear relationships between variables, and where we have limited theory specifying how the variables are related.

A major insight emerging from the machine learning literature is that it is possible to infer some aspects of causal structure with very general assumptions. The set of conditional independences in a non-experimental data set indicates some causal structures are more likely than others. In addition, there are subtle asymmetries in the relationship between the joint distribution of cause and effect and the distributions of cause given effect and effect given cause. These clues are the key to causal discovery algorithms, which attempt to learn causal structure from non-experimental data. I am particularly interested in combining causal discovery techniques with reinforcement learning. In cases where you can do experiments, but there are a large number of variables on which you could intervene, causal discovery techniques should help guide which experiment to perform next by reducing the search space over plausible causal structures. I am also investigating methods to incorporate structural priors into causal discovery algorithms to bridge the gap between causal discovery and the causal effect estimation techniques currently applied in social science and economics.

The Microsoft Graduate Women's Scholarship would enable me to attend conferences early in my research career and make an extended visit to one of the key centres for causal inference in Europe,which would not otherwise be possible due to the high cost of travel from Australia and of childcare for my young daughter overseas.