The goal of this thesis to connect and unify these key approaches. I introduce causal bandit problems: a framework that combines causal graphical models, which were developed for observational causal inference, with multi-armed bandit problems, which are a subset of reinforcement learning problems that are simple enough to admit formal analysis. I show that knowledge of the causal structure allows us to transfer information learned about the outcome of one action to predict the outcome of an alternate action, yielding a novel form of structure between bandit arms that cannot be exploited by existing algorithms. I propose an algorithm for causal bandit problems and prove bounds on the simple regret demonstrating it is close to mini-max optimal and strictly better than algorithms that do not use the additional causal information.

Contributions

The goal of this thesis is to connect and unify the key approaches to solving causal problems from both the observational and interventional viewpoints. My major contribution is a framework that unifies the causal graphical model approach for inference in observational settings with the sequential experimental approach encapsulated by multi-armed bandits. This framework allows us to represent knowledge of how variables are related to one-another in a very natural way and induces an interesting and novel form of structure between the different actions modelled in the bandit problem. I develop a new algorithm that can exploit this structure as a first step towards a unified approach to decision making under uncertainty.

In chapter 4, I introduce causal bandit problems: a framework that unifies causal graphical models with multi-armed bandit problems. Bandit arms are related to interventions in a causal graphical model in a very natural way: each multi-armed bandit arm (or action) corresponds to a particular assignment of values to variables within the causal graphical model. I show how the framework can be used to describe a number of existing problems that lie in the intersection between the observational and interventional approaches to

causality and demonstrate how problems reduce to different flavours of the bandit problem depending what information is observable and when.

In this chapter, I introduce a very general framework that connects causal graphical models with multi-armed bandit problems and demonstrate how it can be leveraged to make better decisions.

A framework to connect bandit problems with observational causal inference

This setting reduces to a contextual bandit problem in our causal bandit framework.

The classical K-armed stochastic bandit problem can be recovered in our framework by considering a simple causal model with one edge connecting a single variable X that can take on K values to a reward variable Y ∈ {0, 1} where P (Y = 1|X) = r(X) for some arbitrary but unknown, real-valued function r.

Our framework bears a superficial similarity to contextual bandit problems, § 3.2.4, since the extra observations on non-intervened variables might be viewed as context for selecting an intervention. However, a crucial difference is that in our model the extra observations are only revealed after selecting an intervention and hence cannot be used as context.

I have developed a framework that formally connects causal graphical models with banditproblems in a very natural way and demonstrated that this framework encodes some keyexisting problems in the literature. I showed that knowledge of the causal structure (butnot the functional relationships) between variables can induce a novel form of structure between alternate actions and that an algorithm that leverages this structure obtains better performance that one that does not.

This work represents an important first step towards a unified approach to causal inference and optimal decision making. There is much exciting work remaining to be done.

Although the causal bandit framework can capture contextual information as well as post-action feedback, I have formally analysed and developed algorithms only for the latter.