Natalia H. Gardiol: Research Statement

In the field of Artificial Intelligence, the problem of planning has been a fundamental research area since the inception of the field. It addresses decision-making at its most basic: how can an artificial agent identify the best sequence of states and actions in order to achieve a goal? And how can it do so when its environment may change in both expected and unexpected ways?

Unfortunately, even in the seemingly simplest formal setting, planning has been found to be a PSPACE-complete problem [?]. Nonetheless, given a deterministic environment and a small amount of problem-specific information, traditional AI planning techniques have been able to make headway in very large state spaces, largely due to powerful first-order logical representations that enable structural features of the state and action spaces to be exploited for efficiency.

In contrast, work in the operations research (OR) community has developed the framework of Markov decision processes (MDPs) [?] to specifically address uncertainty in dynamical systems. This is a key requirement for any system to be applicable to a wide range of real-world problems. However, a large number of states in combination with many uncertain actions yields too large a decision space for standard techniques to handle at once.

In my thesis research, I sought to integrate the AI and OR approaches by building on the strengths of each in turn: we bootstrap a complex probabilistic decision-making problem from a deterministic approximation of the original problem. As computational resources permit, the algorithm explores the states surrounding the initial, approximate, solution, incrementally making its plan more robust. A principal advantage over either traditional approach is a systematic way to trade off the quality of behavior for speed of response; the ability to begin acting as quickly as possible and to improve with time is an asset in many domains. We showed substantial efficiency gains in several benchmark planning problems and in a novel military logistics problem derived from the U.S. Naval Research Lab's TIELT challenge domain [?].

So far, the main theme in my work has been exploiting structure to solve sequential decision-making tasks: when states are represented as collections of objects and the relationships between them, and the transition function mapping one environment state to the next is expressed in terms of the objects' features, instead of their identities, an entire class of transitions can be represented compactly. Objects sharing the same features can be treated as an abstract class, instead of requiring a transition rule for each individual. A great deal of work has shown that harnessing structure in planning leads to great improvements in efficiency and accuracy (e.g., [**?**, **?**, **?**, **?**]).

Nevertheless, techniques for acquiring such structure automatically by interacting with the environment are not yet well understood. For the next steps in my work, I want to address this learning problem, particularly in environments in which the observations only offer a partial hint about the true state of the system (so-called *partial observability*). This issue arises in the interactions of a variety of agents, for example: the intentions of others are generally not observable, but the real world demands that we collaborate or compete effectively. Progress in this direction will require, in particular, use of powerful Bayesian methods, whose strengths are in combining concisely expressed prior knowledge and with experience acquired on-the-fly [**?**, **?**, **?**]. There is an immediate and broad range of applications for this research, including massive-scale electronic auctions, search engines and information retrieval, robotics, and clinical trials in drug design and patient treatments.

Working with professors Nando de Freitas and Kevin Leyton-Brown in the Computer Science department at UBC would provide an exceptional chance to tackle these areas. Professor de Freitas's work in mathematical models for large scale prediction and classification specifically addresses how to make predictions about a world that we only observe in small bits at a time. Professor Leyton-Brown's work on distributed systems of multiple competitive agents addresses the related issue of how artificial agents might model each other when information is limited. Their complementary expertise would be an invaluable resource in investigating decision-making systems that behave effectively in a complex, changing world.