Pradeep Varakantham — Research Statement

My research goal is to build large-scale intelligent systems (both single- and multi-agent) that reason with uncertainty in complex, real-world environments. I foresee an integration of such systems in many critical facets of human life ranging from intelligent assistants in hospitals to offices, to rescue agents in large scale disaster response to sensor agents tracking weather phenomena in earth observing sensor webs, and others. My long-term plan is to make this integration successful, primarily by understanding the fundamental principles of decision making in the presence of uncertainty and applying these principles in building single- and multi-agent systems.

Two major obstacles in building such systems are choosing rich models to represent the underlying uncertainty and reasoning with these models. Uncertainty is the only certainty there is, when dealing with complex, real-world environments. It arises due to non-deterministic outcomes of actions as well as limited or faulty sensors but also due to unknownness of the environment and uncertainty in the actions or motivations of other agents (when interacting with other agents). Thus, providing expressive models to represent all the uncertainties accurately is a key problem that needs to be addressed. Choosing an expressive model however leads to the second major obstacle: the more expressive the model, the higher the complexity involved in solving the model and the less expressive the model (not representing all the uncertainties), the more difficult it is to capture the domain accurately (required if these systems are to make decisions that affect our daily life). Due to the significant computational complexity involved in solving these models optimally, efficiency can often be achieved only by sacrificing solution quality.

This leads to a fundamental tradeoff between expressivity of the model, efficiency of techniques and being able to provide guarantees on solution quality. My research focusses on providing quality-bounded approximations that efficiently solve expressive models. In contrast, previous research has often failed to provide quality bounds, or dealt with inexpressive models. In my thesis, I have addressed this tradeoff in the context of partially observable domains that also have uncertainty about outcomes to actions, by employing a Partially Observable Markov Decision Problem (POMDP) model for single-agent domains and a Distributed POMDP model for multi-agent domains. My contributions are explained below:

Uncertain single-agent domains: POMDPs

The focus here was to provide quality bounded approximations in single-agent POMDPs where there is uncertainty due to non-deterministic outcomes of actions, noisy observations and unknown starting state. Previous research has either focussed on approximate techniques that do not provide any guarantees on decision quality or exact techniques that cannot scale to complex problems. My first contribution, presented in [2], is based on exploiting structure in the dynamics of the domain. For example, if a person is currently at a location, it is highly improbable that the person reaches a location five miles away in the next five seconds. As noted in [2], exploiting such reachability characteristics of the state and belief spaces yields significant improvements in performance. Furthermore, our lagrangian techniques allow for polynomial computation of bounds on the reachable belief space. The second technique, presented in [1], provides for approximation in the value space. The idea in this technique is to compute policies that are at most ϵ (input approximation parameter) away from the optimal. This is the only technique that provides for quality bounded approximation, while obtaining a better run-time performance than one of the fastest existing POMDP solvers, PBVI (as illustrated in [1]). A combination of these two techniques provides for efficient, quality-bounded solutions to solving POMDPs and was employed in building automated assistants that aid humans in office environments.

[1] P. Varakantham, R. Maheswaran, T. Gupta and M. Tambe. Towards efficient computation of quality bounded solutions in POMDPs. In *Proceedings of the Twentieth International Joint Conference on Artificial Intelligence (IJCAI)*, 2007.

[2] P. Varakantham, R. Maheswaran, and M. Tambe. Exploiting belief bounds: Practical POMDPs for personal assistant agents. In *Proceedings of the fourth International Conference on Autonomous Agents and Multi Agent Systems (AAMAS)*, 2005.

Uncertain multi-agent domains: Distributed POMDPs

Distributed POMDPs are important to model domains that have multiple coordinating agents, which are required to take decisions in the presence of uncertainty due to non-deterministic outcomes of actions, noisy observations and unknown starting state. Previous research in the field has focussed on computing optimal solutions to less expressive models or approximate solutions (with no guarantees on solution quality) to more expressive models. I have addressed this issue by providing a combination of techniques that allow for quality bounded and efficient decision making in distributed POMDPs: (a) Exploiting the locality in interactions between the agents towards efficient policy computation[1, 3]; (b) Using an MDP based heuristic function to perform branch-and-bound search in the joint policy space [1]; and (c) Marrying continuous initial belief space techniques for single agent POMDP techniques to existing distributed POMDP techniques to account for uncertainty about the starting state [2]. The utility of these techniques was illustrated in computing decisions (over time) for sensor agents that are required to track stochastically moving targets in a partially observable environment.

[1] P. Varakantham, J. Marecki, M. Tambe and M. Yokoo. Letting loose a SPIDER on a network of POMDPs: Generating quality guaranteed policies. **Submitted to** *the fifth International Conference on Autonomous Agents and Multi Agent Systems (AAMAS)*, 2007.

[2] P. Varakantham, R. Nair, M. Tambe and M. Yokoo. Winning back the CUP for Distributed POMDPs: Planning over continuous belief spaces.. In *Proceedings of the fifth International Conference on Autonomous Agents and Multi Agent Systems, (AAMAS)*, 2006.

[3] R. Nair, P. Varakantham, M. Tambe and M. Yokoo. Networked Distributed POMDPs: A Synthesis of Distributed Constraint Optimization and POMDPs. In *Proceedings of the Twentieth National Conference on Artificial Intelligence (AAAI)*, 2005.

Future Research

For agents and multiagent systems to finally break out in the real-world, in a very fundamental sense, they must conquer uncertainty. In the future, I would like to build upon the work in my thesis towards understanding the reasoning process in ever more realistic environments.

- *Environments with cooperation and competition*: Previous work in distributed POMDPs and multiagent systems in general has categorized agents as either fully adversarial or completely collaborative. However, in many real-world applications, such stark categorization may not be appropriate; agents' motivations thus themselves become sources of uncertainty. Modeling such uncertainties in Distributed Markov Decision Problems and Distributed POMDPs is an open question in the field.

- *Unknown environments*: These are domains where there is no model available or there is uncertainty about the model itself, thus requiring a learning phase to reduce the uncertainty about the model.

- *Bounded resource environments*: These domains are constrained by the limited availability of resources. There is uncertainty introduced in such domains because actions result in non-deterministic consumption of resources. Decision process in such domains becomes complicated due to this underlying uncertainty and the constraints imposed by the resource availability.

I believe that understanding the process of decision making in these critical settings and utilizing this knowledge towards building intelligent agent/multi-agent systems will result in a smooth transition of intelligent systems into our daily life.