Acting under Uncertainty for Information Gathering and Shared Autonomy

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Abstract

Acting under uncertainty is a fundamental challenge for any decision maker in the real world. As uncertainty is often the culprit of failure, many prior works attempt to reduce the problem to one with a known state. However, this fails to account for a key property of acting under uncertainty: we can often gain utility while uncertain. This thesis presents methods that utilize this property in two domains: active information gathering and shared autonomy.

For active information gathering, we present a general framework for reducing uncertainty just enough to make a decision. To do so, we formulate the Decision Region Determination (DRD) problem, modelling how uncertainty impedes decision making. We present two methods for solving this problem, differing in their computational efficiency and performance bounds. We show that both satisfy adaptive submodularity, a natural diminishing returns property that imbues efficient greedy policies with near-optimality guarantees. Empirically, we show that our methods outperform those which reduce uncertainty without considering how it affects decision making.

For shared autonomy, we first show how the general problem of assisting with an unknown user goal can be modelled as one of acting under uncertainty. We then present our framework, based on Hindsight Optimization or QMDP, enabling us assist for a distribution of user goals by minimizing the expected cost. We evaluate our framework on real users, demonstrating that our method achieves goals faster, requires less user input, decreases user idling time, and results in fewer user-robot collisions than those which rely on predicting a single user goal. Finally, we extend our framework to learn how user behavior changes with assistance, and incorporate this model into cost minimization.