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DRAFT: MODERN ADAPTIVE CONTROL AND REINFORCEMENT LEARNING

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JAB: My first book was dedicated to my teachers; this one I dedicate to the students from whom I've learned still more.

Prelude

This book is an edited collection of lecture notes from classes given by Drew Bagnell at Carnegie Mellon University in the class *Adaptive Control and Reinforcement Learning* (2010,11,14), from Byron Boots at Georgia Tech (2019) and from Sanjiban Choudhury at Cornell (2022). We thank Chris Atkeson for co-teaching the first instance of this class and shaping how we think about the problems herein. We gratefully acknowledge the many students who took (and put up with!) incomplete notes on the topics covered. We thank Arun Venkatraman who provided the step-by-step derivation of iLQR, and Anqi Li, who provided key editing and improvements to this document.

This book– and the classes it was built from– was designed to provide a set of practical tools to build decision making procedures for machines interacting with the world. Our applications vary from video games and web-search to robot manipulation and self-driving vehicles. The field is vast and so our take is necessarily just one narrow viewpoint. We explicitly make no attempt to be rigorous, but rather focus on intuition and informal mathematical argument to build that intuition, and on techniques we've seen work multiple times on hard decision making problems. We try to outline the techniques and ways of thinking we'd be most likely to pull out in practice. Throughout, we attempt to point to rigorous derivations and the original literature on the topics.

Naturally this work is presented in a somewhat personal context, noting the practical and theoretical differences that arose in implementing real systems. These notes are by no means exhaustive nor is it meant to serve as a summary of the outstanding work in the field; the interested reader will hopefully follow the related reading and bibliography to dive deeper. Instead, it is meant to summarize lessons we've learned, particularly in close collaboration with others in robotics and learning, on problems of making decisions.

These notes were designed to build on essential techniques in probability (conditional probability, conditional independence, Gaussians, integration techniques, Bayesian methods and inference, filtering and time-series models), linear algebra (both computational and basic linear analysis), optimization (gradients, Hessians, metrics, Krylov sub-spaces), and machine learning (generalization, optimization, no-regret/online learning, back-propagation, and kernel methods).

A companion set of lectures notes, covering elements of those techniques particularly in learning and probability, *Statistical Techniques in Robotics* is under development to fill the gap.