

# Contents

<b>1</b>	<b>Introduction</b>	<b>1</b>
1.1	The dynamic programming and reinforcement learning problem . . . . .	2
1.2	Approximation in dynamic programming and reinforcement learning	5
1.3	About this book . . . . .	8
<b>2</b>	<b>An introduction to dynamic programming and reinforcement learning</b>	<b>11</b>
2.1	Introduction . . . . .	11
2.2	Markov decision processes . . . . .	14
2.2.1	Deterministic setting . . . . .	14
2.2.2	Stochastic setting . . . . .	19
2.3	Value iteration . . . . .	23
2.3.1	Model-based value iteration . . . . .	23
2.3.2	Model-free value iteration and the need for exploration . . . . .	28
2.4	Policy iteration . . . . .	30
2.4.1	Model-based policy iteration . . . . .	31
2.4.2	Model-free policy iteration . . . . .	37
2.5	Policy search . . . . .	38
2.6	Summary and discussion . . . . .	41
<b>3</b>	<b>Dynamic programming and reinforcement learning in large and continuous spaces</b>	<b>43</b>
3.1	Introduction . . . . .	43
3.2	The need for approximation in large and continuous spaces . . . . .	47
3.3	Approximation architectures . . . . .	49
3.3.1	Parametric approximation . . . . .	49
3.3.2	Nonparametric approximation . . . . .	51
3.3.3	Comparison of parametric and nonparametric approximation	53
3.3.4	Remarks . . . . .	54
3.4	Approximate value iteration . . . . .	54
3.4.1	Model-based value iteration with parametric approximation	55
3.4.2	Model-free value iteration with parametric approximation . . . . .	58
3.4.3	Value iteration with nonparametric approximation . . . . .	62
3.4.4	Convergence and the role of nonexpansive approximation . . . . .	63
3.4.5	Example: Approximate Q-iteration for a DC motor . . . . .	66
3.5	Approximate policy iteration . . . . .	71
3.5.1	Value iteration-like algorithms for approximate policy evaluation . . . . .	73

3.5.2	Model-free policy evaluation with linearly parameterized approximation . . . . .	74
3.5.3	Policy evaluation with nonparametric approximation . . . . .	84
3.5.4	Model-based approximate policy evaluation with rollouts . . . . .	84
3.5.5	Policy improvement and approximate policy iteration . . . . .	85
3.5.6	Theoretical guarantees . . . . .	88
3.5.7	Example: Least-squares policy iteration for a DC motor . . . . .	90
3.6	Finding value function approximators automatically . . . . .	95
3.6.1	Basis function optimization . . . . .	96
3.6.2	Basis function construction . . . . .	98
3.6.3	Remarks . . . . .	100
3.7	Approximate policy search . . . . .	101
3.7.1	Policy gradient and actor-critic algorithms . . . . .	102
3.7.2	Gradient-free policy search . . . . .	107
3.7.3	Example: Gradient-free policy search for a DC motor . . . . .	109
3.8	Comparison of approximate value iteration, policy iteration, and policy search . . . . .	113
3.9	Summary and discussion . . . . .	114
<b>4</b>	<b>Approximate value iteration with a fuzzy representation</b>	<b>117</b>
4.1	Introduction . . . . .	117
4.2	Fuzzy Q-iteration . . . . .	119
4.2.1	Approximation and projection mappings of fuzzy Q-iteration	119
4.2.2	Synchronous and asynchronous fuzzy Q-iteration . . . . .	123
4.3	Analysis of fuzzy Q-iteration . . . . .	127
4.3.1	Convergence . . . . .	127
4.3.2	Consistency . . . . .	135
4.3.3	Computational complexity . . . . .	140
4.4	Optimizing the membership functions . . . . .	141
4.4.1	A general approach to membership function optimization . .	141
4.4.2	Cross-entropy optimization . . . . .	143
4.4.3	Fuzzy Q-iteration with cross-entropy optimization of the membership functions . . . . .	144
4.5	Experimental study . . . . .	145
4.5.1	DC motor: Convergence and consistency study . . . . .	146
4.5.2	Two-link manipulator: Effects of action interpolation, and comparison with fitted Q-iteration . . . . .	152
4.5.3	Inverted pendulum: Real-time control . . . . .	157
4.5.4	Car on the hill: Effects of membership function optimization	160
4.6	Summary and discussion . . . . .	164
<b>5</b>	<b>Approximate policy iteration for online learning and continuous-action control</b>	<b>167</b>
5.1	Introduction . . . . .	167
5.2	A recapitulation of least-squares policy iteration . . . . .	168

5.3	Online least-squares policy iteration . . . . .	170
5.4	Online LSPI with prior knowledge . . . . .	173
5.4.1	Online LSPI with policy approximation . . . . .	174
5.4.2	Online LSPI with monotonic policies . . . . .	175
5.5	LSPI with continuous-action, polynomial approximation . . . . .	177
5.6	Experimental study . . . . .	180
5.6.1	Online LSPI for the inverted pendulum . . . . .	180
5.6.2	Online LSPI for the two-link manipulator . . . . .	192
5.6.3	Online LSPI with prior knowledge for the DC motor . . . . .	195
5.6.4	LSPI with continuous-action approximation for the inverted pendulum . . . . .	198
5.7	Summary and discussion . . . . .	201
<b>6</b>	<b>Approximate policy search with cross-entropy optimization of basis functions</b>	<b>205</b>
6.1	Introduction . . . . .	205
6.2	Cross-entropy optimization . . . . .	207
6.3	Cross-entropy policy search . . . . .	209
6.3.1	General approach . . . . .	209
6.3.2	Cross-entropy policy search with radial basis functions . . . . .	213
6.4	Experimental study . . . . .	216
6.4.1	Discrete-time double integrator . . . . .	216
6.4.2	Bicycle balancing . . . . .	223
6.4.3	Structured treatment interruptions for HIV infection control	229
6.5	Summary and discussion . . . . .	233
<b>Appendix A</b>	<b>Extremely randomized trees</b>	<b>235</b>
A.1	Structure of the approximator . . . . .	235
A.2	Building and using a tree . . . . .	236
<b>Appendix B</b>	<b>The cross-entropy method</b>	<b>239</b>
B.1	Rare-event simulation using the cross-entropy method . . . . .	239
B.2	Cross-entropy optimization . . . . .	242
<b>Symbols and abbreviations</b>		<b>245</b>
<b>Bibliography</b>		<b>249</b>
<b>List of algorithms</b>		<b>267</b>
<b>Index</b>		<b>269</b>