Model Predictive Control and Reinforcement Learning

– Summer School 2021 – Joschka Boedecker and Moritz Diehl

For the multiple choice questions, which give exactly one point, tick exactly one box for the right answer.

1. Which of the following functions $f(x), f : \mathbb{R}^n \to \mathbb{R}$, is NOT convex $(c \in \mathbb{R}^n, A \in \mathbb{R}^{m \times n})$?

(a) x $ Ax _2^2 + \log(c^\top x)$	(b) $\ \ Ax\ _2^2 + \exp(c^\top x)$	(c) $\Box c^{\top}x + \exp(\ Ax\ _2^2)$	(d) $\Box -c^{\top}x + \ Ax\ _2^2$
			1

2. The local convergence rate of Newton's method is:

(a) superlinear	(b) x quadratic	(c) linear	(d) sublinear
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3. A point in the feasible set of an NLP that satisfies the KKT optimality conditions is

(a) the global minimum	(b) a boundary point
(c) a local minimum	(d) x a candidate for local minimum
	1

4. What is the most general (unconstrained) problem type to which the Gauss-Newton Hessian approximation is applicable?

(a) x non-linear least squares objective	(b) linear least-squares objective		
(c) linear objective	(d) any convex objective		
	1		

5. How does CasADi compute derivatives?

(a) Finite differences	(b) Imaginary trick
(c) X Algorithmic Differentiation	(d) Symbolic Differentiation
	1

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6. How many optimization variables does the NLP arising in the direct **multiple shooting** method have, if the system has n_x states, n_u controls, the initial value is fixed, and the time horizon is divided into N control intervals (piecewise-constant)?

(a) $\square Nn_u$	(b) $\square Nn_x^3 + Nn_u^2$	(c) \mathbf{x} $(N+1)n_x + Nn_u$	(d) $\qquad \frac{1}{3}N^3n_u^3$	
				1

7. Regard an MPC optimization problem for N = 10 steps of the discrete time system s* = 2s + a with continuous state s ∈ ℝ and continuous bounded control action a ∈ [-1,1]. The stage cost is given by c(s,a) = a² and the terminal cost by E(s) = 100s². The initial state is s₀. To which optimization problem class does the problem belong?

(a) Linear Programming (LP)	(b) Mixed Integer Programming (MIP) but not LP
(c) X Quadratic Programming (QP) but not LP	(d) Nonlinear Programming (NLP) but not QP
	1

8. Regard an MPC optimization problem for N = 10 steps of the discrete time system s⁺ = 2s² + a with continuous state s ∈ ℝ and continuous bounded control action a ∈ [-1, 1]. The stage cost is given by c(s, a) = a² and the terminal cost by E(s) = 100s². The initial state is s
₀. To which optimization problem class does the problem belong?

(a) Linear Programming (LP)	(b) Mixed Integer Programming (MIP) but not LP
(c) Quadratic Programming (QP) but not LP	(d) X Nonlinear Programming (NLP) but not QP
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9. Regard dynamic programming for the discrete time system $s^+ = s + a$ with continuous state $s \in \mathbb{R}$ and continuous bounded control action $a \in [-1, 1]$, with zero stage cost c(s, a) = 0. We apply one step of dynamic programming (with operator T) to the value function $J_1(s) = \max(0, s)$. What is the resulting function $J_0 = TJ_1$?

(a) $x J_0(s) = \max(0, s - 1)$	(b) $\Box J_0(s) = \max(0, s+1)$
(c) $\Box J_0(s) = 0$	(d) $\Box J_0(s) = \max(s - 1, s + 1)$
	1

10. What is meant by monotonicity of DP? Formulate it using T as the DP operator, acting on value functions J and J'.

(a) $\boxed{\mathbf{x}} J' \ge J \Rightarrow TJ' \ge TJ$	(b) $\Box J' \leq J \Rightarrow TJ' \geq TJ$
(c) $\Box TJ' \ge TJ \Rightarrow J' \le J$	(d) $\Box TJ' \leq TJ \Rightarrow J' \leq J$

11. Which of the following components is not part of an MDP specification?

(a) Set of states	(b) Set of rewards	(c) x Policy	(d) Set of actions
			1

12. Imagine you want to apply the algorithms from this lecture on a real physical system. You get sensor input after each 0.05 seconds, but the execution of actions has a delay of 0.2 seconds. Is the Markov property fulfilled?

(a) No	(b) Yes	(c) X Yes, if a history of	(d) Only if a function
		the last 0.2 seconds is added to the state space	approximator is used for the value function
			1

13. With what could you derive/calculate the value function $v_{\pi}(s)$ from the action-value function $q_{\pi}(s, a)$:

(a) With the Markov	(b) x With the policy π	(c) Not possible	(d) Only possible with
Decision Process (MDP)			both the MDP and the pol-
			icy π

14. Why is Q-learning an off-policy method?

(a) \square Because using an ϵ -greedy policy changes actions	(b) Because Q-learning uses a bootstraped value, instead	
randomly	of a Monte-Carlo rollout	
(c) Because we learn Q-values instead of a policy	(d) x Because we learn Q-values for the greedy policy, while using a different policy to interact with the environment.	
	1	

15. The correct Q-Learning update is:

$ \begin{array}{c c} (\mathbf{a}) \ \square \ Q(s,a) \ \leftarrow \ Q(s,a) + \alpha[r + \gamma \max_{a^{\star}} Q(s,a^{\star}) - Q(s',a^{\star})] \end{array} $	(b) \mathbf{x} $Q(s,a) \leftarrow Q(s,a) + \alpha [r + \gamma \max_{a^{\star}} Q(s',a^{\star}) - Q(s,a)]$
$\fbox{(c)} \ \fbox{Q(s,a)} \leftarrow Q(s,a) + \alpha[r + \gamma Q(s',a) - Q(s',a)]$	(d) $\square Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma Q(s',a) - Q(s,a)]$
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16. What can you control with the ϵ of an ϵ -greedy policy?

1

1

17. Target networks were introduced in order to:

(a) Introduce correla-	(b) Prevent forgetting past experiences	(c) x Avoid oscillations	(d) Make RL problems
tions into the sequence of		during training which slow	less like Supervised Learn-
observations		down learning	ing problems
			1

18. In policy gradient methods, what should a baseline ideally depend on?

(a) x On the state	(b) On the action	(c) On state and action	(d) On nothing (i.e. it
			should be constant)
			1

19. Which of the following is true for Actor-Critic algorithms:

	(b) X They reduce gradi-	(c) The usage of base-	(d) The actor learns a
problems with discrete ac-	ent variance usually occur-	lines is compulsory for vari-	value function and the critic
tions	ring in vanilla PG methods	ance reduction	learns a policy

20. We use experience replay to:

(a) Introduce correla- tions into the sequence of observations	(b) x Prevent forgetting past experiences	(c) Avoid oscillations during the learning process	(d) Break the curse of dimensionality
			1

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