## Model Predictive Control and Reinforcement Learning

Summer School 2021 –Joschka Boedecker and Moritz Diehl

Fo	For the multiple choice questions, which give exactly one point, tick exactly one box for the right answer.					
1.	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)	(b)	(c)			
				1		
2.	2. The local convergence rate of Newton's method is:					
	(a) superlinear	(b) linear	(c) sublinear	(d) quadratic		
				1		
3.	A point in the feasible set of an	NLP that satisfies the KKT opting	nality conditions is			

1

the global minimum

a local minimum

(a) a candidate for local minimum

a boundary point

1

4.	what is the most general (unconstrained) problem type to which	the Gauss-Newton Hessian approximation is applicable?		
	(a) linear least-squares objective	(b) non-linear least squares objective		
	(c) linear objective	(d) any convex objective		
		1		
5.	How does CasADi compute derivatives?			
	(a) Algorithmic Differentiation	(b) Imaginary trick		
	(c) Symbolic Differentiation	(d) Finite differences		
		1		
6.	How many optimization variables does the NLP arising in the d $n_u$ controls, the initial value is fixed, and the time horizon is div			
	(a) $\square Nn_x^3 + Nn_u^2$ (b) $\square Nn_u$	(c)		
		1		
7.	Regard an MPC optimization problem for $N=10$ steps of the discrete time system $s^*=2s+a$ with continuous state $s\in\mathbb{R}$ and continuous bounded control action $a\in[-1,1]$ . The stage cost is given by $c(s,a)=a^2$ and the terminal cost by $E(s)=100s^2$ . The initial state is $\bar{s}_0$ . To which optimization problem class does the problem belong?  (a) Linear Programming (LP)			
		(d) Quadratic Programming (QP) but not LP		
	(c) Nonlinear Programming (NLP) but not QP	(u) Quadratic Frogramming (QF) but not EF		
		1		
8.	Regard an MPC optimization problem for $N=10$ steps of the discrete time system $s^+=2s^2+a$ with continuous state $s\in\mathbb{R}$ and continuous bounded control action $a\in[-1,1]$ . The stage cost is given by $c(s,a)=a^2$ and the terminal cost by $E(s)=100s^2$ The initial state is $\bar{s}_0$ . To which optimization problem class does the problem belong?			
	(a) Linear Programming (LP)	(b) Quadratic Programming (QP) but not LP		
	(c) Mixed Integer Programming (MIP) but not LP	(d) Nonlinear Programming (NLP) but not QP		
		1		
9.	Regard dynamic programming for the discrete time system $s^+$ control action $a \in [-1,1]$ , with zero stage cost $c(s,a) = 0$ . We value function $J_1(s) = \max(0,s)$ . What is the resulting function	apply one step of dynamic programming (with operator $T$ ) to the		
9.	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		
9.	control action $a \in [-1, 1]$ , with zero stage cost $c(s, a) = 0$ . We value function $J_1(s) = \max(0, s)$ . What is the resulting function	apply one step of dynamic programming (with operator $T$ ) to the n $J_0=TJ_1$ ?		

(a) $\Box TJ' \ge TJ \Rightarrow J' \le J$	(b) $\Box TJ' \leq TJ \Rightarrow J' \leq J$
(c)	(d) $\Box J' \geq J \Rightarrow TJ' \geq TJ$
	1

Points on page (max. 1)

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

2. 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) Only if a function approximator is used for the	(b) Yes	(c) Yes, if a history of	(d) No	
value function		the last 0.2 seconds is added to the state space		
			1	
13. With what could you derive/cald	culate the value function $v_{\pi}(s)$ fr	com the action-value function $q_{\pi}$	(s,a):	
(a) $\square$ With the policy $\pi$	(b) With the Markov	(c) Only possible with	(d) Not possible	
	Decision Process (MDP)	both the MDP and the pol-		
	, , ,	icy $\pi$		
			1	
14. Why is Q-learning an off-policy method?				
(a) $\square$ Because using an $\epsilon$ -g	(a) $\square$ Because using an $\epsilon$ -greedy policy changes actions randomly		(b) Because we learn Q-values instead of a policy	
randomly				
(c) Because Q-learning uses a bootstraped value, instead of a Monte-Carlo rollout		(d) 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:

(a) $\square$ $Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma Q(s',a) - Q(s',a)]$	(b) $\square Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma Q(s',a) - Q(s,a)]$
(c) $\square Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a^*} Q(s,a^*) -$	(d) $Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a^*} Q(s',a^*) - Q(s',a)]$
$Q(s', a^{\star})]$	Q(s,a)]
	1

ze o neth
1

17. Target networks were introduced	d in order to:		
(a) Prevent forgetting	(b) Make RL problems	(c) Avoid oscillations	(d) Introduce correla-
past experiences	less like Supervised Learn-	during training which slow	tions into the sequence of
	ing problems	down learning	observations
			1
18. In policy gradient methods, wha	t should a baseline ideally deper	nd on?	
(a) On the action	(b) On nothing (i.e. it	(c) On the state	(d) On state and action
	should be constant)		
			1
19. Which of the following is true for	or Actor-Critic algorithms:		
(a) The actor learns a	(b) Can be used only in	(c) The usage of base-	(d) They reduce gradi-
value function and the critic	problems with discrete ac-	lines is compulsory for vari-	ent variance usually occur-
learns a policy	tions	ance reduction	ring in vanilla PG methods
			1
20. We use experience replay to:			
(a) Prevent forgetting	(b) Introduce correla-	(c) Avoid oscillations	(d) Break the curse of
past experiences	tions into the sequence of	during the learning process	dimensionality
	observations		
			1

## **Empty page for calculations**