Surname, Name, ID number: ________________________________

Autonomous and Mobile Robotics M

26 January 2023 - Theory

Some questions may have more than one correct answers: for each question, indicate all the correct answers.

1. A *non-holonomic* constraint:
   - ⊗ cannot be fully integrated
   - ○ can be written in the configuration space
   - ⊗ does not restrict the space of configurations but the instant robot mobility
2. In a trajectory following problem, the robot must asymptotically perform a desired trajectory
   - ⊗ that depends on a free parameter s
   - ○ that depends on time t
   - ○ that must be represented by a polynomial function
3. In map-based navigation, the robot:
   - ⊗ plans the trajectory using a map of the environment
   - ○ must update the planned path on the based of sensor information
   - ○ navigates the environment on the base of the sensor information only
4. Sequential Monte-Carlo Localization:
   - ⊗ is based on the simultaneous evaluation of multiple potential robot configurations called particles;
   - ⊗ resamples the particles on the based of the weights evaluated after prediction, innovation and normalization;
   - ○ works only in case the robot configuration can be described by a Gaussian distribution.
5. The future discounted reward is defined as:
   - ○ $G_t = R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + \cdots = \sum_{i=0}^{\infty} \gamma^i R_{t+i}$
   - ⊗ $G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots = \sum_{i=0}^{\infty} \gamma^i R_{t+i+1}$
   - ○ $G_t = R_{t-1} + \gamma R_{t-2} + \gamma^2 R_{t-3} + \cdots = \sum_{i=0}^{\infty} \gamma^i R_{t-i-1}$
6. The Bellman optimality equation for the action value function can be written as
   - ○ $q_*(s,a) = \max v_\pi(s)$
   - ⊗ $q_*(s,a) = \mathbb{E}_*[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} | S_t = s, A_t = a]$
   - ○ $q_*(s,a) = p(s', r|s,a)\,[r + \gamma \max_{a' \in \mathcal{A}} q_*(s', a')]$
7. Monte-Carlo reinforcement learning:
   - ○ can be applied to non-episodic tasks
   - ○ requires the knowledge of the reward model
   - ⊗ does not require the knowledge of the transition model
8. Under which hypotheses Monte-Carlo reinforcement learning methods converge to optimal value function?
   - ⊗ infinite episodes
   - ○ deterministic policy
   - ⊗ exploring starts
9. In backward view Sarsa(λ), the elegibility trace update can be defined as
   - ○ $E_t(s) = \gamma E_{t-1}(s) + \lambda(S_t = s)$
   - ○ $E_t(s) = \gamma\lambda E_{t-1}(s) + 1(S_t = s)$
   - ⊗ $E_t(s,a) = \gamma\lambda E_{t-1}(s,a) + 1(S_t = s, A_t = a)$
10. TD(λ) with Value Function Approximation is defined as
    - ○ $\Delta\mathbf{w} = \alpha(G_t - \hat{v}(S_t, \mathbf{w}))\nabla_{\mathbf{w}}\hat{v}(S_t, \mathbf{w})$
    - ○ $\Delta\mathbf{w} = \alpha(R_{t+1} + \gamma\hat{v}(S_{t+1}, \mathbf{w}) - \hat{v}(S_t, \mathbf{w}))\nabla_{\mathbf{w}}\hat{v}(S_t, \mathbf{w})$
    - ⊗ $\Delta\mathbf{w} = \alpha(G_t^\lambda - \hat{v}(S_t, \mathbf{w}))\nabla_{\mathbf{w}}\hat{v}(S_t, \mathbf{w})$

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26 January 2023 - Exercise

The student is asked to solve the following problem.

Let us consider a fully observable and deterministic environment with 5 states $s_{\{1,\ldots,5\}}$.

s_1	s_2	s_3	s_4	s_5

- Action set : {TryLeft, TryRight}
- Rewards:
  - +1 in state s_1
  - -2 in state s_3
  - +4 in state s_5
  - 0 in all other states
- Transition model:
  - $p(s_1|s_1, \text{TryLeft}) = p(s_5|s_5, \text{TryRight}) = 1$
  - $p(s_1|s_1, \text{TryRight}) = p(s_2|s_1, \text{TryRight}) = 0.5$
  - $p(s_1|s_2, \text{TryLeft}) = p(s_2|s_2, \text{TryLeft}) = 0.5$
  - $p(s_2|s_2, \text{TryRight}) = p(s_3|s_2, \text{TryRight}) = 0.5$
  - ...
- Policy: $\pi(\text{TryLeft}|s_{\{1,\ldots,5\}}) = \pi(\text{TryRight}|s_{\{1,\ldots,5\}}) = 0.5$
- Discount factor $\gamma = 1$

Starting from an arbitrary initialisation of the state value function, compute the first iteration of the state value function evaluation provided by a Dynamic Programming algorithm with asyncronous backup assuming the random policy π.

$v_\pi(s_1)$	$v_\pi(s_2)$	$v_\pi(s_3)$	$v_\pi(s_4)$	$v_\pi(s_5)$

Solution:

The state value function is initialized to 0 for all the states.

$v_\pi(s_1)$	$v_\pi(s_2)$	$v_\pi(s_3)$	$v_\pi(s_4)$	$v_\pi(s_5)$
0.75	-0.0625	-1.0156	0.2461	3.0615