Your grade: 100%

Your latest: **100%** • Your highest: **100%** • To pass you need at least 80%. We keep your highest score.

Next item →

1. Which of the following is true about policy-based methods? (**Select all that apply**) — 1 / 1 point

- [x] Policy-based methods are useful in problems where the policy is easier to approximate than action-value functions.

  Correct
  Correct. For example in the Mountain Car problem a good policy is easy to represent whereas the value function is complex.

- [x] Policy-based methods allow smooth improvement in the policy without drastic changes.

  Correct
  Correct. As the policy parameters change the action probabilities change smoothly, but with value-based methods a small change in action-value function can drastically change the action probabilities.

- [x] Policy-based methods can learn an optimal policy that is stochastic.

  Correct
  Correct. It can learn a stochastic optimal policy, such as the soft-max in action preferences.

- [x] Policy-based methods can be applied to continuous action space domains.

  Correct
  Correct. By parameterizing a policy to represent a probability distribution such as Gaussian, it can be applied to continuous action space domains.

2. Which of the following statements about parameterized policies are true? (**Select all that apply**) — 1 / 1 point

- [x] For each state, the sum of all the action probabilities must equal to one.

  Correct
  Correct! This condition is necessary for the function to be a valid probability distribution.

- [x] The probability of selecting any action must be greater than or equal to zero.

  Correct
  Correct! This is one of the conditions for a valid probability distribution.

- [ ] The policy must be approximated using linear function approximation.
- [ ] The function used for representing the policy must be a softmax function.

3. Assume you're given the following preferences $h_1 = 44, h_2 = 42$, and $h_3 = 38$, corresponding to three different actions (a_1, a_2, a_3), respectively. Under a softmax policy, what is the probability of choosing a_2, rounded to three decimal numbers? — 1 / 1 point

- ( ) 0.002
- ( ) 0.879
- (•) 0.119
- ( ) 0.42

  Correct
  Correct!

4. Which of the following is true about softmax policy? (Select all that apply) — 1 / 1 point

- [x] It can be parameterized by any function approximator as long as it can output scalar values for each available action, to form a softmax policy.

  Correct
  Correct. It can use any function approximation from deep artificial neural networks to simple linear features.

- [ ] It cannot represent an optimal policy that is stochastic, because it reaches a deterministic policy as one action preference dominates others.
- [ ] Similar to epsilon-greedy policy, softmax policy cannot approach a deterministic policy.
- [x] It is used to represent a policy in discrete action spaces.

- [x] It is used to represent a policy in discrete action spaces.

Correct
Correct!

5. What are the differences between using softmax policy over action-values and using softmax policy over action-preferences? (**Select all that apply**)

1 / 1 point

- [x] When using softmax policy over action-values, even if the optimal policy is deterministic, the policy may never approach a deterministic policy.

Correct
Correct. The policy will always select proportional to exponentiated action-values.

- [ ] When using softmax policy over action-values, assuming a tabular representation, the policy will converge to the optimal policy regardless of whether the optimal policy is stochastic or deterministic.
- [x] When using softmax policy over action-preferences, assuming a tabular representation, the policy will converge to the optimal policy regardless of whether the optimal policy is stochastic or deterministic.

Correct
Correct. Action-preferences does not approach specific values like action-values do. They can be driven to produce a stochastic policy or deterministic policy.

6. What is the following objective, and in which task formulation?

1 / 1 point

$$r(\pi) = \Sigma_s \mu(s) \Sigma_a \pi(a|s,\theta) \Sigma_{s',r} p(s',r|s,a) r$$

- ( ) Undiscounted return objective, episodic task
- ( ) Average reward objective, episodic task
- ( ) Discounted return objective, continuing task
- (•) Average reward objective, continuing task

Correct
Correct.

7. The following equation is the outcome of the policy gradient theorem. Which of the following is true about the policy gradient theorem? (Select all that apply)

1 / 1 point

$$\nabla r(\pi) = \Sigma_s \mu(s) \Sigma_a \nabla \pi(a|s,\theta) q_\pi(s,a)$$

- [x] This expression can be converted into:

$$\mathbb{E}_\pi[\Sigma_a \nabla \pi(a|S,\theta) q_\pi(S,a)]$$

In discrete action space, by approximating q_pi we could also use this gradient to update the policy.

Correct
Correct. The expression contains sum over actions, which can be computed for discrete actions. In the textbook, this is also called the all-actions method.

- [x] The true action value q_π can be approximated in many ways, for example using TD algorithms.

Correct
Correct.

- [x] This expression can be converted into the following expectation over π:

$$\mathbb{E}_\pi[\nabla \ln \pi(A|S,\theta) q_\pi(S,A)]$$

Correct
Correct. In fact, this expression is normally used to perform stochastic gradient updates.

- [x] We do not need to compute the gradient of the state distribution μ.

Correct
Correct.

8. Which of the following statements is true? (**Select all that apply**)

1 / 1 point

- [x] Subtracting a baseline in the policy gradient update tends to reduce the variance of the update, which results in faster learning.

Correct
Correct.

- [ ] TD methods do not have a role when estimating the policy directly.

- [x] To update the actor in Actor-Critic, we can use TD error in place of q_π in the Policy Gradient Theorem.

> **Correct**
> Correct. This is equivalent to using one-step state value and subtracting a current state value baseline.

- [x] The Actor-Critic algorithm consists of two parts: a parameterized policy — the actor — and a value function — the critic.

> **Correct**
> Correct.

9. We usually want the critic to update at a faster rate than the actor. **1 / 1 point**

- (•) True
- ( ) False

> **Correct**
> Correct!

10. Consider the following state features and parameters θ for three different actions (red, green, and blue): **1 / 1 point**

$$\mathbf{X}(s)=\begin{bmatrix}0.1\\0.3\\0.6\end{bmatrix} \qquad \boldsymbol{\theta}=\begin{bmatrix}45\\73\\21\\120\\120\\-10\\-100\\200\\-25\end{bmatrix}\begin{matrix}\left.\vphantom{\begin{matrix}1\\1\\1\end{matrix}}\right\}a_0\\ \left.\vphantom{\begin{matrix}1\\1\\1\end{matrix}}\right\}a_1\\ \left.\vphantom{\begin{matrix}1\\1\\1\end{matrix}}\right\}a_2\end{matrix}$$

Compute the action preferences for each of the three different actions using linear function approximation and stacked features for the action preferences.

What is the action preference of a_0 (red)?

- (•) 39
- ( ) 33
- ( ) 35
- ( ) 37

> **Correct**
> Correct.

11. Which of the following statements are true about the Actor-Critic algorithm with softmax policies? (**Choose all that apply**) **1 / 1 point**

- [x] The learning rate parameter of the actor and the critic can be different.

> **Correct**
> Correct! In practice, it is preferable to have a slower learning rate for the actor so that the critic can accurately critique the policy.

- [ ] The actor and the critic share the same set of parameters.
- [x] Since the policy is written as a function of the current state, it is like having a different softmax distribution for each state.

> **Correct**
> Correct!

- [ ] The preferences must be approximated using linear function approximation.

12. Which one is a reasonable parameterization for a Gaussian policy?

1 / 1 point

- ○ μ: the exponential of a linear function of parameters, σ: a linear function of parameters.
- ○ μ: a linear function of parameters, σ: a linear function of parameters
- ◉ μ: a linear function of parameters, σ: the exponential of a linear function of parameters.

Correct
Correct!