

1. Let $f(x, y) = (x + y)^2 + e^{xy}$. Recall that the gradient is composed of the partial derivatives for each variable

$$\nabla f(x, y) = \begin{bmatrix} \frac{\partial f(x,y)}{\partial x} \\ \frac{\partial f(x,y)}{\partial y} \end{bmatrix}$$

where $\frac{\partial f(x,y)}{\partial x}$ is the derivative of $f(x, y)$ w.r.t. x assuming that y is fixed.

- (a) What is $\nabla f(x, y)$ for the f defined above? Hint: Recall that the derivative of e^z is e^z .
 - (b) What is $\nabla f(0, 1)$?
2. Find the gradient of f
- (a) if $f(x, y, z) = \frac{y^z}{x}$
 - (b) if $f(x) = e^{x^2+5}$
 - (c) if $f(\mathbf{x}) = \mathbf{x}^T \beta$ where \mathbf{x} is a vector in \mathbb{R}^N and β is a vector of constants in \mathbb{R}^N
 - (d) if $f(\mathbf{x}) = (\mathbf{x}^T \beta - y)^2$ where \mathbf{x} is a vector in \mathbb{R}^N , β is a vector of constants in \mathbb{R}^N , and y is a scalar in \mathbb{R}
3. (*Exercise 9.1 S&B*) Show that tabular methods such as presented in Course 2 of the MOOC (and Part I of the book) are a special case of linear function approximation. What would the feature vectors be?

4. Assume we are given a fixed policy π . Recall that the mean-squared value error is

$$\overline{\text{VE}}(\mathbf{w}) = \sum_{s \in \mathcal{S}} \mu(s) (v_\pi(s) - \hat{v}(s, \mathbf{w}))^2.$$

Recall that we can use TD with linear function approximation to learn parameters \mathbf{w} :

$$\mathbf{w} \leftarrow \mathbf{w} + \alpha [R_{t+1} + \gamma \mathbf{w}^\top \mathbf{x}(S_{t+1}) - \mathbf{w}^\top \mathbf{x}(S_t)] \mathbf{x}(S_t).$$

When linear TD converges, it converges to what we call the TD fixed-point. Let's denote the weight vector found by linear TD at convergence as \mathbf{w}_{TD} . We denote the estimated value as $\hat{v}(s, \mathbf{w}_{\text{TD}}) = \mathbf{w}_{\text{TD}}^\top \mathbf{x}(s)$. At the TD fixed point, we know that the VE is within a bounded expansion of the lowest possible error:

$$\overline{\text{VE}}(\mathbf{w}_{\text{TD}}) \leq \frac{1}{1 - \gamma} \min_{\mathbf{w}} \overline{\text{VE}}(\mathbf{w})$$

- (a) Recall that $\min_{\mathbf{w}} \overline{\text{VE}}(\mathbf{w})$ is the minimal value error you can achieve under this value function parameterization. If we have a tabular parameterization, then what might $\min_{\mathbf{w}} \overline{\text{VE}}(\mathbf{w})$ be? What if the parameterization is a state aggregation?
- (b) If $\gamma = 0.9$ and $\min_{\mathbf{w}} \overline{\text{VE}}(\mathbf{w}) = 0$, then what is the minimum and maximum value of $\overline{\text{VE}}(\mathbf{w}_{\text{TD}})$?
- (c) If $\gamma = 0.9$ and $\min_{\mathbf{w}} \overline{\text{VE}}(\mathbf{w}) = 1$, then what is the minimum and maximum value of $\overline{\text{VE}}(\mathbf{w}_{\text{TD}})$?
- (d) If $\gamma = 0.99$ and $\min_{\mathbf{w}} \overline{\text{VE}}(\mathbf{w}) = 1$, then what is the minimum and maximum value of $\overline{\text{VE}}(\mathbf{w}_{\text{TD}})$?
- (e) We have seen that if we can perfectly represent the value function, then $\min_{\mathbf{w}} \overline{\text{VE}}(\mathbf{w}) = 0$. How about the other direction: if $\min_{\mathbf{w}} \overline{\text{VE}}(\mathbf{w}) = 0$, then does that mean we can represent true value function?
- (f) **Challenge Question:** Imagine instead we obtained the asymptotic solution under the Monte carlo update; let us call this \mathbf{w}_{MC} . This is the solution we would obtain after updating with many many pairs of states and sampled returns, with s sampled proportionally to μ . How is $\overline{\text{VE}}(\mathbf{w}_{\text{MC}})$ and $\min_{\mathbf{w}} \overline{\text{VE}}(\mathbf{w})$ related? Hint: Try to write down the objective for Monte carlo and reason about the solution to this objective.

5. **Challenge Question:** Recall that the mean-squared value error is

$$\overline{\text{VE}}(\mathbf{w}) = \sum_{s \in \mathcal{S}} \mu(s) (v_\pi(s) - \hat{v}(s, \mathbf{w}))^2.$$

We discussed one choice for μ , which is to use the state visitation under the behavior policy. Namely, as the policy is executed in the state, the weighting $\mu(s)$ is proportional to how frequently the agent is in state s . What are some other weightings could be used instead?