

4 0.5 3

NO No matter how θ_0 and θ_1 are initialized, so long as α is sufficiently small, we can safely expect gradient descent to converge to the same solution. Correct 0.25

This is not true, because depending on the initial condition, gradient descent may end up

YES If the learning rate is too small, then gradient descent may take a very long time to converge. Correct 0.25

If the learning rate is small, gradient descent ends up taking an extremely small step

YES If θ_0 and θ_1 are initialized at the global minimum, the one iteration will not change their values. Correct 0.25

At the global minimum, the derivative (gradient) is zero, so gradient descent will not

NO Setting the learning rate α to be very small is not harmful, and can only speed up convergence. Correct 0.25

If the learning rate is small, gradient descent ends up taking an extremely small step

If θ_0 and θ_1 are initialized at a local minimum, the one iteration will not change their values. Incorrect 0.00

At a local minimum, the derivative (gradient) is zero, so gradient descent will not change the parameters.

YES If the first few iterations of gradient descent cause $f(\theta_0, \theta_1)$ to increase rather than decrease, then the most likely cause is that we have set the learning rate α to too large a value. Incorrect 0.00 If α were small enough, then gradient descent should always successfully take a tiny small downhill and decrease $f(\theta_0, \theta_1)$ at least a little bit.

If gradient descent instead increases the objective value, that means α is too large

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This is not true, because depending on the initial condition, gradient descent may end up

NO Even if the learning rate α is very large, every iteration of gradient descent will decrease the objective value. Incorrect 0.00 If the learning rate α is too large, one step of gradient descent can actually increase the objective value

YES If θ_0 and θ_1 are initialized so that $\theta_0 = \theta_1$, then by symmetry (because we do simultaneous updates to both), the updates to θ_0 and θ_1 are different (even though we're doing simultaneous updates). Incorrect 0.00

Suppose that for some linear regression problem (say, predicting housing prices as in the example above), you have managed to find some θ_0, θ_1 such that $J(\theta_0, \theta_1) = 0$. Which of the following statements is true?

Your Answer Score Explanation

NO We can perfectly predict the value of y even for new examples that we have not yet seen.
 Incorrect 0.00 Even though we can fit our training set perfectly, this does not mean that

NO This is not possible: By the definition of $J(\theta_0, \theta_1)$, it is not possible for there to exist θ_0 and θ_1 such that $J(\theta_0, \theta_1) = 0$.
 Correct 0.25 If all of our training examples lie perfectly on a line, then $J(\theta_0, \theta_1) = 0$ is possible.

YES Our training set can be fit perfectly by a straight line, i.e., all of our training examples lie on a line.
 Incorrect 0.00 If $J(\theta_0, \theta_1) = 0$, that means the line defined by the equation " $y = \theta_0 + \theta_1 x$ " perfectly fits all of our data.

NO Gradient descent is likely to get stuck at a local minimum and fail to find the global minimum.
 Incorrect 0.00 The cost function $J(\theta_0, \theta_1)$ for linear regression has no local optima (other than the global minimum).

NO For this to be true, we must have $y(i) = 0$ for every value of $i = 1, 2, \dots, m$.
 Correct 0.25 So long as all of our training examples lie on a straight line, we will be able to find θ_0 and θ_1 such that $J(\theta_0, \theta_1) = 0$.
 NO For this to be true, we must have $\theta_0 = 0$ and $\theta_1 = 0$ so that $h_{\theta}(x) = 0$ for all x .
 Correct 0.25

If $J(\theta_0, \theta_1) = 0$, that means the line defined by the equation " $y = \theta_0 + \theta_1 x$ " perfectly fits all of our data. There's no particular reason to expect that the values of θ_0 and θ_1 that achieve this are both 0 (unless $y(i) = 0$ for all of our training examples).

NO This is not possible: By the definition of $J(\theta_0, \theta_1)$, it is not possible for there to exist θ_0 and θ_1 so that $J(\theta_0, \theta_1) = 0$.
 Correct 0.25 If all of our training examples lie perfectly on a line

, then $J(\theta_0, \theta_1) = 0$ is possible.

YES Gradient descent is likely to get stuck at a local minimum and fail to find the global minimum.
 Incorrect 0.00 The cost function $J(\theta_0, \theta_1)$ for linear regression has no local optima (other than the global minimum), so gradient descent will not get stuck at a bad local minimum.

NO Our training set can be fit perfectly by a straight line, i.e., all of our training examples lie on a line.
 Incorrect 0.00
 If $J(\theta_0, \theta_1) = 0$, that means the line defined by the equation " $y = \theta_0 + \theta_1 x$ " perfectly fits all of our data.

YES For these values of θ_0 and θ_1 that satisfy $J(\theta_0, \theta_1) = 0$, we have that $h(x(i)) = y(i)$ for all i .
 Incorrect 0.00 $J(\theta_0, \theta_1) = 0$, that means the line defined by the equation " $y = \theta_0 + \theta_1 x$ " perfectly fits all of our data.