Feedback — II. Linear regression with one variable

Help

You submitted this quiz on **Wed 30 Oct 2013 11:47 AM PDT (UTC -0700)**. You got a score of **4.00** out of **5.00**. You can attempt again in 10 minutes.

Question 1

Consider the problem of predicting how well a student does in her second year of college/university, given how well they did in their first year. Specifically, let x be equal to the number of "A" grades (including A-. A and A+ grades) that a student receives in their first year of college (freshmen year). We would like to predict the value of y, which we define as the number of "A" grades they get in their second year (sophomore year).

Questions 1 through 4 will use the following training set of a small sample of different students' performances. Here each row is one training example. Recall that in linear regression, our hypothesis is $h_\theta(x) = \theta_0 + \theta_1 x$, and we use m to denote the number of training examples.

x	y
3	4
2	1
4	3
0	1

For the training set given above, what is the value of m? In the box below, please enter your answer (which should be a number between 0 and 10).

You entered:

1

Your Answer	Score	Explanation

1	✖	0.00	
Total		0.00 / 1.00	

Question Explanation

m is the number of training examples. In this example, we have m=4 examples.

Question 2

For this question, continue to assume that we are using the training set given above. Recall our definition of the cost function was $J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$. What is $J(0, 1)$? In the box below, please enter your answer (use decimals instead of fractions if necessary, e.g., 1.5).

You entered:

0.5

Your Answer		Score	Explanation
0.5	✔	1.00	
Total		1.00 / 1.00	

Question Explanation

When $\theta_0 = 0$ and $\theta_1 = 1$, we have $h_\theta(x) = \theta_0 + \theta_1 x = x$. So,

$$\begin{aligned} J(\theta_0, \theta_1) &= \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2 \\ &= \frac{1}{2*4} ((1)^2 + (1)^2 + (1)^2 + (1)^2) \\ &= \frac{4}{8} \\ &= 0.5 \end{aligned}$$

Question 3

Suppose we set $\theta_0 = -2, \theta_1 = 0.5$. What is $h_\theta(6)$?

You entered:

1

Your Answer		Score	Explanation
1	✔	1.00	
Total		1.00 / 1.00	

Question Explanation

Setting $x = 6$, we have $h_\theta(x) = \theta_0 + \theta_1 x = -2 + 0.5 * 6 = 1$

Question 4

Let f be some function so that $f(\theta_0, \theta_1)$ outputs a number. For this problem, f is some arbitrary/unknown smooth function (not necessarily the cost function of linear regression, so f may have local optima). Suppose we use gradient descent to try to minimize $f(\theta_0, \theta_1)$ as a function of θ_0 and θ_1. Which of the following statements are true? (Check all that apply.)

Your Answer		Score	Explanation
☑ If the learning rate is too small, then gradient descent may take a very long time to converge.	✔	0.25	If the learning rate is small, gradient descent ends up taking an extremely small step on each iteration, and therefore can take a long time to converge.
☐ If θ_0 and θ_1 are initialized so that $\theta_0 = \theta_1$, then by symmetry (because we do simultaneous updates to the two parameters), after one iteration of gradient descent, we will still have $\theta_0 = \theta_1$.	✔	0.25	The updates to θ_0 and θ_1 are different (even though we're doing simultaneous updates), so there's no particular reason to expect them to be the same after one iteration of gradient descent.

☑ If θ_0 and θ_1 are initialized at the global minimum, the one iteration will not change their values.	✔	0.25	At the global minimum, the derivative (gradient) is zero, so gradient descent will not change the parameters.
☐ 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.	✔	0.25	This is not true, because depending on the initial condition, gradient descent may end up at different local optima.
Total		1.00 / 1.00	

Question 5

Suppose that for some linear regression problem (say, predicting housing prices as in the lecture), we have some training set, and for our training set we managed to find some θ_0, θ_1 such that $J(\theta_0, \theta_1) = 0$. Which of the statements below must then be true? (Check all that apply.)

Your Answer		Score	Explanation
☐ We can perfectly predict the value of y even for new examples that we have not yet seen. (e.g., we can perfectly predict prices of even new houses that we have not yet seen.)	✔	0.25	Even though we can fit our training set perfectly, this does not mean that we'll always make perfect predictions on houses in the future/on houses that we have not yet seen.
☑ Our training set can be fit perfectly by a straight line, i.e., all of our training examples lie	✔	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.

perfectly on some straight line.			
Gradient descent is likely to get stuck at a local minimum and fail to find the global minimum.	✔	0.25	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.
For this to be true, we must have $y^{(i)} = 0$ for every value of $i = 1, 2, \ldots, m$.	✔	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 so that $J(\theta_0, \theta_1) = 0$. It is not necessary that $y^{(i)} = 0$ for all of our examples.
Total		1.00 / 1.00	