Feedback — VI. Logistic Regression

Help

You submitted this quiz on **Mon 31 Mar 2014 5:38 PM PDT**. You got a score of **5.00** out of **5.00**.

Question 1

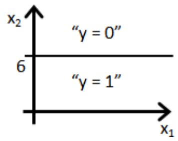
Suppose that you have trained a logistic regression classifier, and it outputs on a new example x a prediction h_\theta(x) = 0.4. This means (check all that apply):

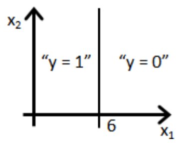
Your Answer		Score	Explanation
☐ Our estimate for P(y=0|x;\theta) is 0.4.	✔	0.25	h_\theta(x) is P(y=1|x;\theta), not P(y=0|x;\theta)
☐ Our estimate for P(y=1|x;\theta) is 0.6.	✔	0.25	h_\theta(x) gives P(y=1|x;\theta), not 1 - P(y=1|x;\theta).
☑ Our estimate for P(y=1|x;\theta) is 0.4.	✔	0.25	h_\theta(x) is precisely P(y=1|x;\theta), so each is 0.4.
☑ Our estimate for P(y=0|x;\theta) is 0.6.	✔	0.25	Since we must have P(y=0|x;\theta) = 1 - P(y=1|x;\theta), the former is 1 - 0.4 = 0.6.
Total		1.00 / 1.00	

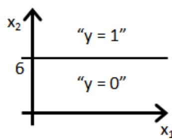
Question 2

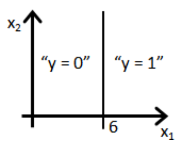
Suppose you train a logistic classifier h_\theta(x) = g(\theta_0 + \theta_1x_1 + \theta_2 x_2). Suppose \theta_0 = - 6, \theta_1 = 1, \theta_2 = 0. Which of the following figures represents the decision boundary found by your classifier?

Your Answer	Score	Explanation









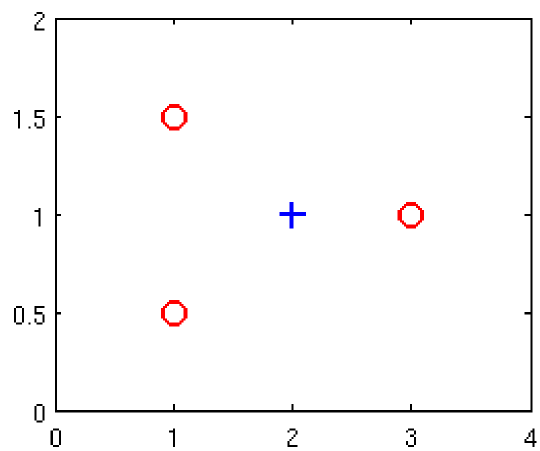
1.00 In this figure, we transition from negative to positive when x_1 goes from below 6 to above 6 which is true for the given values of \theta.

Total 1.00 / 1.00

Question 3

Suppose you have the following training set, and fit a logistic regression classifier h_\theta(x) = g(\theta_0 + \theta_1x_1 + \theta_2 x_2).

x_1	x_2	y
1	0.5	0
1	1.5	0
2	1	1
3	1	0



Which of the following are true? Check all that apply.

Your Answer		Score	Explanation
☐ Because the positive and negative examples cannot be separated using a straight line, linear regression will perform as well as logistic regression on this data.	✔	0.25	While it is true they cannot be separated, logistic regression will outperform linear regression since its cost function focuses on classification, not prediction.
☑ At the optimal value of \theta (e.g., found by fminunc), we will have J(\theta) \geq 0.	✔	0.25	The cost function J(\theta) is always non-negative for logistic regression.
☐ Adding polynomial features (e.g., instead using h_\theta(x) = g(\theta_0 + \theta_1x_1 + \theta_2 x_2 + \theta_3 x_1^2 + \theta_4 x_1 x_2 + \theta_5 x_2^2)) would increase J(\theta) because we are now summing over more terms.	✔	0.25	The summation in J(\theta) is over examples, not features. Furthermore, the hypothesis will now be more accurate (or at least just as accurate) with new features, so the cost function will decrease.
☑ Adding polynomial features (e.g., instead using	✔	0.25	Adding new features can only improve the fit on the training set: since setting \theta_3 = \theta_4 = \theta_5 = 0 makes the hypothesis the same as the original one, gradient descent will use those features (by making the corresponding \theta_j

h_\theta(x) = g(\theta_0 + \theta_1x_1 + \theta_2 x_2 + \theta_3 x_1^2 + \theta_4 x_1 x_2 + \theta_5 x_2^2)) could increase how well we can fit the training data.			non-zero) only if doing so improves the training set fit.
Total		1.00 / 1.00	

Question 4

For logistic regression, the gradient is given by \frac{\partial}{\partial \theta_j} J(\theta) = \sum_{i=1}^m{ (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)}}. Which of these is a correct gradient descent update for logistic regression with a learning rate of \alpha? Check all that apply.

Your Answer		Score	Explanation
☑ \theta := \theta - \alpha \frac{1}{m} \sum_{i=1}^m{ (h_\theta(x^{(i)}) - y^{(i)}) x^{(i)}} .	✔	0.25	This is a vectorized version of the direct substitution of \frac{\partial}{\partial \theta_j} J(\theta) into the gradient descent update.
☑ \theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^m{ (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)}} (simultaneously update for all j).	✔	0.25	This is a direct substitution of \frac{\partial}{\partial \theta_j} J(\theta) into the gradient descent update.
☐ \theta := \theta - \alpha \frac{1}{m} \sum_{i=1}^m{ \left(\theta^T x - y^{(i)}\right) x^{(i)}} .	✔	0.25	This vectorized version uses the linear regression hypothesis \theta^T x instead of that for logistic regression.
☐ \theta_j := \theta_j - \alpha	✔	0.25	This uses the linear regression hypothesis

\frac{1}{m} \sum_{i=1}^m{ \left(\theta^T x - y^{(i)}\right) x_j^{(i)}} (simultaneously update for all j).			\theta^T x instead of that for logistic regression.
Total		1.00 / 1.00	

Question 5

Which of the following statements are true? Check all that apply.

Your Answer		Score	Explanation
☐ Linear regression always works well for classification if you classify by using a threshold on the prediction made by linear regression.	✔	0.25	As demonstrated in the lecture, linear regression often classifies poorly since its training prodcedure focuses on predicting real-valued outputs, not classification.
☑ The one-vs-all technique allows you to use logistic regression for problems in which each y^{(i)} comes from a fixed, discrete set of values.	✔	0.25	If each y^{(i)} is one of k different values, we can give a label to each y^{(i)} \in \{1, 2, \ldots, k \} and use one-vs-all as described in the lecture.
☐ For logistic regression, sometimes gradient descent will converge to a local minimum (and fail to find the global minimum). This is	✔	0.25	The cost function for logistic regression is convex, so gradient descent will always converge to the global minimum. We still might use a more advanded optimization algorithm since they can be faster and don't require you to select a learning rate.

the reason we prefer more advanced optimization algorithms such as fminunc (conjugate gradient/BFGS/L-BFGS/etc).			
☑ The cost function J(\theta) for logistic regression trained with m \geq 1 examples is always greater than or equal to zero.	✔	0.25	The cost for any example x^{(i)} is always \geq 0 since it is the negative log of a quantity less than one. The cost function J(\theta) is a summation over the cost for each eample, so the cost function itself must be greater than or equal to zero.
Total		1.00 / 1.00	