Feedback — VI. Logistic Regression

You submitted this quiz on **Sat 11 May 2013 2:56 PM PDT -0700**. You got a score of **5.00** out of **5.00**.

Question 1

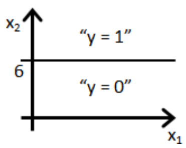
Suppose that you have trained a logistic regression classifier, and it outputs on a new example x a prediction $h_\theta(x)$ = 0.2. This means (check all that apply):

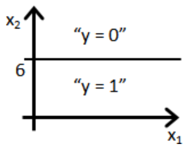
Your Answer		Score	Explanation
☐ Our estimate for $P(y=0\|x;\theta)$ is 0.2.	✔	0.25	$h_\theta(x)$ is $P(y=1\|x;\theta)$, not $P(y=0\|x;\theta)$.
☐ Our estimate for $P(y=1\|x;\theta)$ is 0.8.	✔	0.25	$h_\theta(x)$ gives $P(y=1\|x;\theta)$, not $1-P(y=1\|x;\theta)$.
☑ Our estimate for $P(y=1\|x;\theta)$ is 0.2.	✔	0.25	$h_\theta(x)$ is precisely $P(y=1\|x;\theta)$, so each is 0.2.
☑ Our estimate for $P(y=0\|x;\theta)$ is 0.8.	✔	0.25	Since we must have $P(y=0\|x;\theta)=1-P(y=1\|x;\theta)$, the former is 1 - 0.2 = 0.8.
Total		1.00 / 1.00	

Question 2

Suppose you train a logistic classifier $h_\theta(x)=g(\theta_0+\theta_1x_1+\theta_2x_2)$. Suppose $\theta_0=6, \theta_1=0, \theta_2=-1$. Which of the following figures represents the decision boundary found by your classifier?

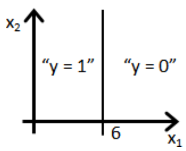
Your Answer	Score	Explanation

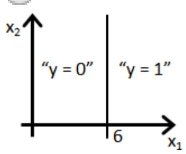




✔ 1.00

In this figure, we transition from negative to positive when x_2 goes from above 6 to below 6 which is true for the given values of θ.



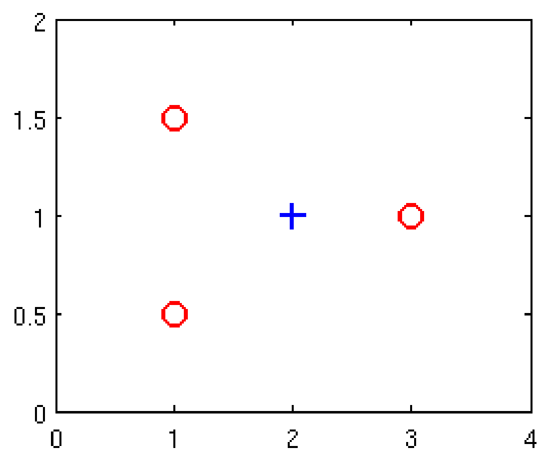


Total 1.00 / 1.00

Question 3

Suppose you have the following training set, and fit a logistic regression classifier $h_\theta(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$.

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
☐ The positive and negative examples cannot be separated using a straight line. So, gradient descent will fail to converge.	✔	0.25	While it is true they cannot be separated, gradient descent will still converge to the optimal fit. Some examples will remain misclassified at the optimum.
☐ 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 θ (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.
☑ $J(\theta)$ will be a convex function, so gradient descent should converge to the global minimum.	✔	0.25	The cost function $J(\theta)$ is guaranteed to be convex for logistic regression.
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 α? Check all that apply.

Your Answer		Score	Explanation
☐ $\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)}) x^{(i)}$ (simultaneously update for all j).	✔	0.25	This incorrectly multiplies by the vector $x^{(i)}$ in the summation rather than just $x_j^{(i)}$.
☐ $\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^{m} \left(\theta^T x - y^{(i)}\right) x_j^{(i)}$ (simultaneously update for all j).	✔	0.25	This uses the linear regression hypothesis $\theta^T x$ instead of that for

			logistic regression.
☑ $\theta := \theta - \alpha \frac{1}{m} \sum_{i=1}^{m} \left(\frac{1}{1+e^{-\theta^T x^{(i)}}} - y^{(i)} \right) x^{(i)}$.	✔	0.25	This is a vectorized version of gradient descent that substitues in the exact form of $h_\theta(x^{(i)})$ used by logistic regression.
☑ $\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)}$ (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.
Total		1.00 / 1.00	

Question 5

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

Your Answer		Score	Explanation
☐ Since we train one classifier when there are two classes, we train two classifiers when there are three classes (and we do one-vs-all classification).	✔	0.25	We need to train three classifiers if there are three classes; each one treats one of the three classes as the $y = 1$ examples and the rest as the $y = 0$ examples.
☑ The sigmoid function $g(z) = \frac{1}{1+e^{-z}}$ is never greater than one (> 1).	✔	0.25	The denomiator ranges from ∞ to 1 as z grows, so the result is always in $(0, 1)$.
☑ 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.
☐ 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.

Total	1.00 / 1.00