Feedback — VI. Logistic Regression

Help

You submitted this quiz on **Tue 1 Apr 2014 7:43 PM IST**. You got a score of **5.00** out of **5.00**.

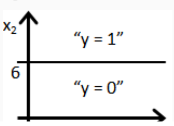
Question 1

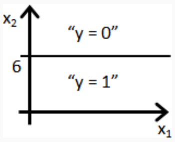
Suppose that you have trained a logistic regression classifier, and it outputs on a new example x a prediction $h_\theta(x)$ = 0.4. This means (check all that apply):

Your Answer		Score	Explanation
☐ Our estimate for $P(y=1\|x;\theta)$ is 0.6.	✔	0.25	$h_\theta(x)$ gives $P(y=1\|x;\theta)$, not $1-P(y=1\|x;\theta)$.
☐ Our estimate for $P(y=0\|x;\theta)$ 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 0.4.	✔	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	

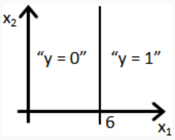
Question 2

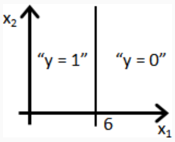
Suppose you train a logistic classifier $h_\theta(x)=g(\theta_0+\theta_1x_1+\theta_2x_2)$. Suppose $\theta_0=6,\theta_1=0,\theta_2=-1$. Which of the following figures represents the decision boundary found by your classifier?

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.



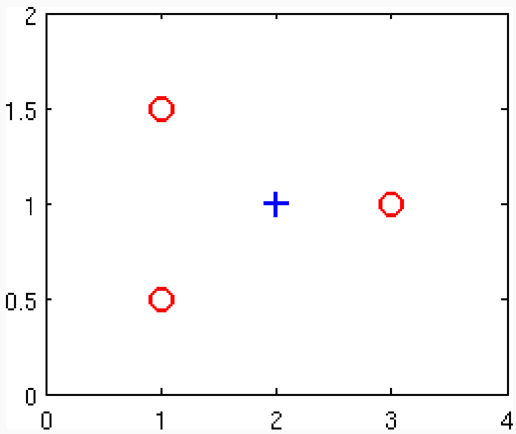


Total 1.00 / 1.00

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
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.
If we train gradient descent for enough iterations, for some examples $x^{(i)}$ in the training set it is possible to obtain $h_\theta(x^{(i)}) > 1$.	✔	0.25	The function $g(z)$ in the hypothesis $h_\theta(x)$ is the sigmoid function

			sigmoid function $\frac{1}{1+e^{-z}}$ which always lies between 0 and 1.
☑ Adding polynomial features (e.g., instead using $h_\theta(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1^2 + \theta_4 x_1 x_2 + \theta_5 x_2^2)$) could increase how well we can fit the training data.	✔	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 θ_j non-zero) only if doing so improves the training set fit.
☐ 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.
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
☑ $\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^{m} \left(\frac{1}{1+e^{-\theta^T x^{(i)}}} - y^{(i)} \right) x_j^{(i)}$	✔	0.25	This substitutes the exact form of $h_\theta(x^{(i)})$ used by logistic regression into the

(simultaneously update for all j).			gradient descent update.
☐ $\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^m \left(h_\theta(x^{(i)}) - y^{(i)}\right) x^{(i)}$ (simultaneously update for all j).	✔	0.25	This incorrectly multiplies by the vector $x^{(i)}$ in the summation rather than just $x_j^{(i)}$.
☐ $\theta := \theta - \alpha \frac{1}{m} \sum_{i=1}^m \left(\theta^T x - y^{(i)}\right) x^{(i)}$.	✔	0.25	This vectorized version uses the linear regression hypothesis $\theta^T x$ instead of that for logistic regression.
☑ $\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^m \left(h_\theta(x^{(i)}) - y^{(i)}\right) x_j^{(i)}$ (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
☑ 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 ≥ 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.
☐ 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.
☐ For logistic regression, sometimes gradient descent will	✔	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

converge to a local minimum (and fail to find the global minimum). This is the reason we prefer more advanced optimization algorithms such as fminunc (conjugate gradient/BFGS/L-BFGS/etc).			select a learning rate.
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.
Total		1.00 / 1.00	