



## Logistic Regression

TOTAL POINTS 5

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):

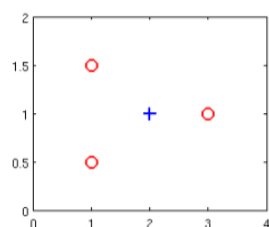
1 point

- ☒ Our estimate for  $P(y = 1|x; \theta)$  is 0.2.
- ☒ Our estimate for  $P(y = 0|x; \theta)$  is 0.8.
- ☐ Our estimate for  $P(y = 1|x; \theta)$  is 0.8.
- ☐ Our estimate for  $P(y = 0|x; \theta)$  is 0.2.

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

1 point

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



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

- ☒ 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.
- ☒ At the optimal value of  $\theta$  (e.g., found by fminunc), we will have  $J(\theta) \geq 0$ .
- ☐ Adding polynomial features (e.g., instead using  $h_\theta(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1^2 + \theta_4 x_1 x_2 + \theta_5 x_2^2)$ ) would increase  $J(\theta)$  because we are now summing over more terms.
- ☐ If we train gradient descent for enough iterations, for some examples  $x^{(i)}$  in the training set it is possible to obtain  $h_\theta(x^{(i)}) > 1$ .

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

1 point

- ☐  $\theta := \theta - \alpha \frac{1}{m} \sum_{i=1}^m (\theta^T x - y^{(i)}) x^{(i)}$ .
- ☐  $\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^m (\theta^T x - y^{(i)}) x_j^{(i)}$  (simultaneously update for all  $j$ ).
- ☐  $\theta := \theta - \alpha \frac{1}{m} \sum_{i=1}^m \left( \frac{1}{1+e^{-\theta^T x^{(i)}}} - y^{(i)} \right) x^{(i)}$ .
- ☐  $\theta := \theta - \alpha \frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) x^{(i)}$ .

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

1 point

- ☐ For logistic regression, sometimes gradient descent will 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).
- ☐ Since we train one classifier when there are two classes, we train two classifiers when there are three

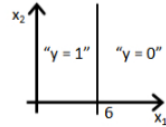
classes (and we do one-vs-all classification).

- ☒ The cost function  $J(\theta)$  for logistic regression trained with  $m \geq 1$  examples is always greater than or equal to zero.
- ☒ 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.

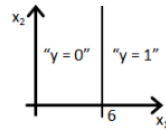
5. Suppose you train a logistic classifier  $h_{\theta}(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$ . Suppose  $\theta_0 = -6, \theta_1 = 1, \theta_2 = 0$ . Which of the following figures represents the decision boundary found by your classifier?

1 point

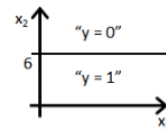
☐ Figure:



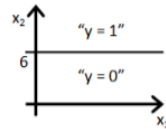
☒ Figure:



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