Suppose that you have trained a logistic regression classifier, and it outputs on a new example x a prediction $h_\theta(x)$ = 0.7. This means (check all that apply):

1 point

- [x] Our estimate for $P(y = 1|x; \theta)$ is 0.7.
- [x] Our estimate for $P(y = 0|x; \theta)$ is 0.3.
- [ ] Our estimate for $P(y = 0|x; \theta)$ is 0.7.
- [ ] Our estimate for $P(y = 1|x; \theta)$ is 0.3.

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

1 point

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

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

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

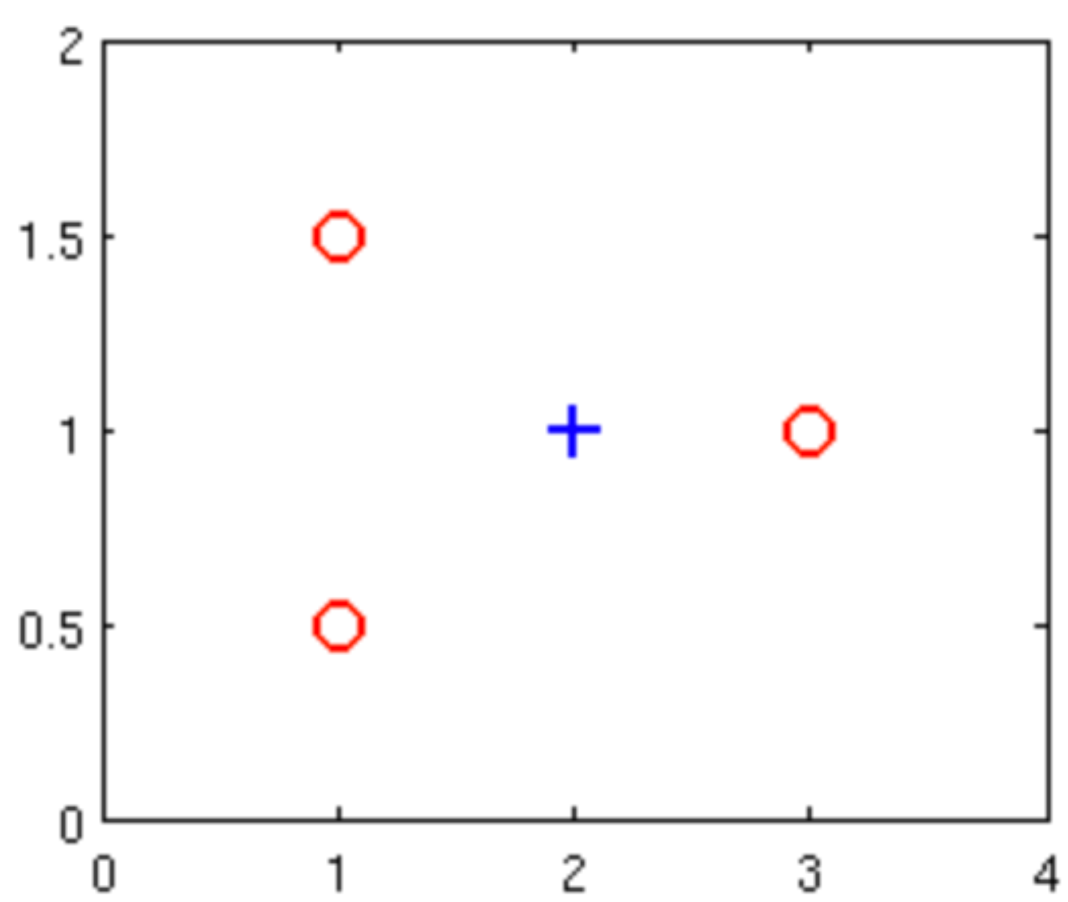
1 point

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

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.

- [x] 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.
- [x] At the optimal value of θ (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 $h_\theta(x^{(i)}) > 1$.

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

1 point

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

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

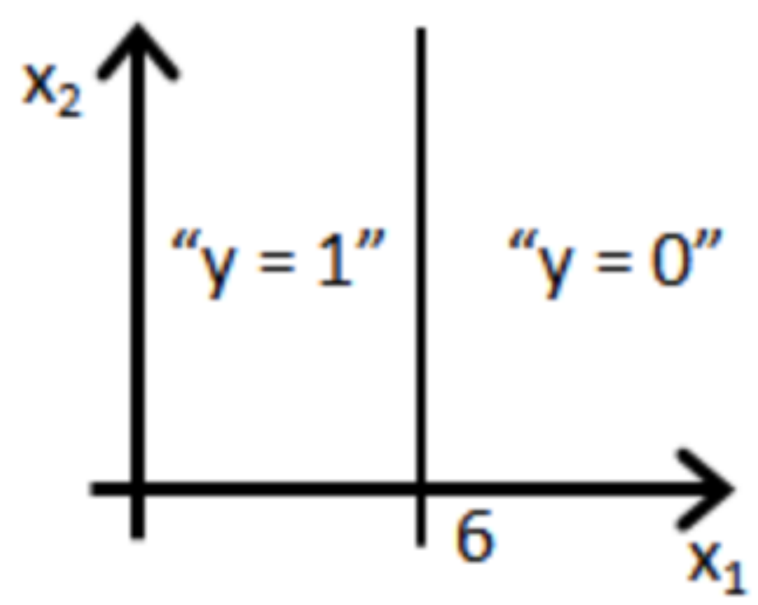
1 point

- [x] The cost function $J(\theta)$ for logistic regression trained with $m \geq 1$ examples is always 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.
- [x] The sigmoid function $g(z) = \frac{1}{1+e^{-z}}$ is never greater than one (> 1).
- [ ] 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).

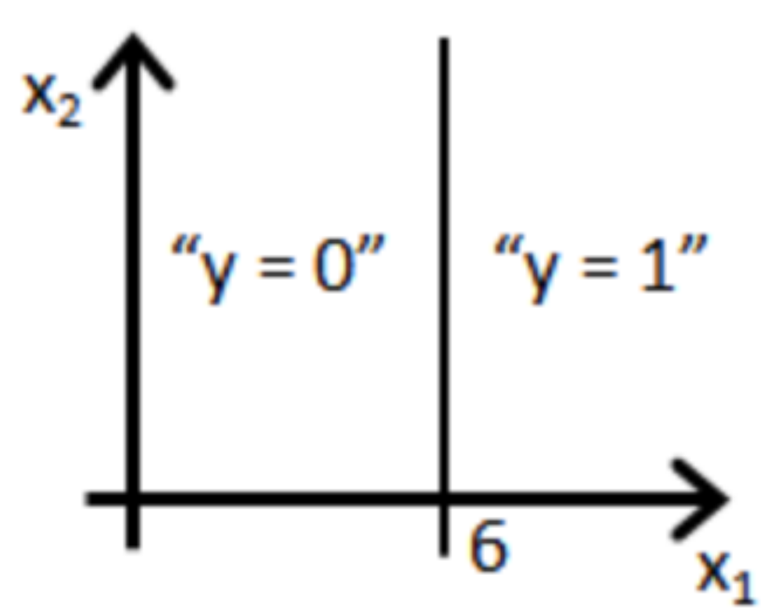
Suppose you train a logistic classifier $h_\theta(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$. Suppose $\theta_0 = 6, \theta_1 = 0, \theta_2 = -1$. Which of the following figures represents the decision boundary found by your classifier?

1 point

- [ ] Figure:



- [ ] Figure:



- [x] Figure: