Logistic Regression

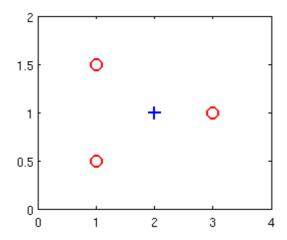
- 1. Suppose that you have trained a logistic regression classifier, and it outputs on a new example x a prediction $h_{\theta}(x) = 0.7$. This means (check all that apply):
 - Our estimate for $P(y = 1 | x; \theta)$ is 0.3.
 - Our estimate for $P(y = 0|x; \theta)$ is 0.7.

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

x_1	<i>x</i> ₂	у
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 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 $h_{\theta}(x^{(i)}) > 1$.

- 3. 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.
 - $\theta_j := \theta_j \alpha \frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) y^{(i)}) x^{(i)}$ (simultaneously update for all j).

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

$$heta_j := heta_j - lpha rac{1}{m} \sum_{i=1}^m \left(rac{1}{1 + e^{- heta T_x(i)}} - y^{(i)}
ight) x_j^{(i)}$$
 (simultaneously update for all j).

- $\theta := \theta \alpha \frac{1}{m} \sum_{i=1}^{m} (\theta^T x y^{(i)}) x^{(i)}$.
- 4. Which of the following statements are true? Check all that apply.

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.

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

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

Figure:

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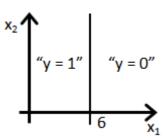


Figure:

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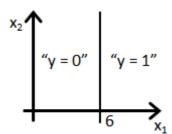


Figure:

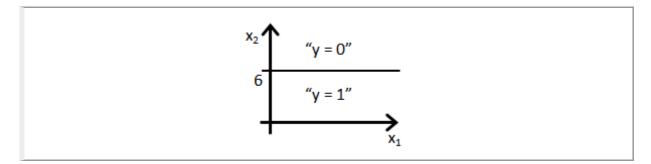


Figure:

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