

Logistic Regression Cost Function and Overfitting

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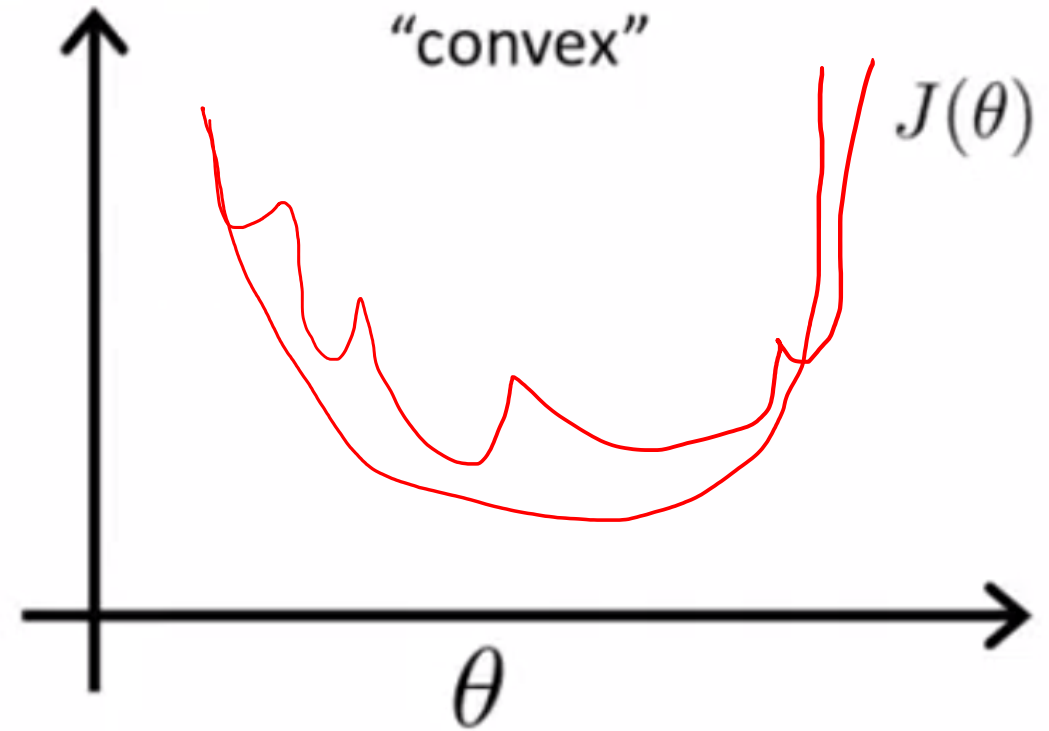
Cost Function for Linear Regression

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^m (h(x) - y)^2$$

$$J(\theta) = \frac{1}{m} \sum_{i=1}^m \frac{1}{2} (h(x) - y)^2$$

$$J(\theta) = \frac{1}{m} \sum_{i=1}^m \text{Cost}(h(x^{(i)}), y^{(i)})$$

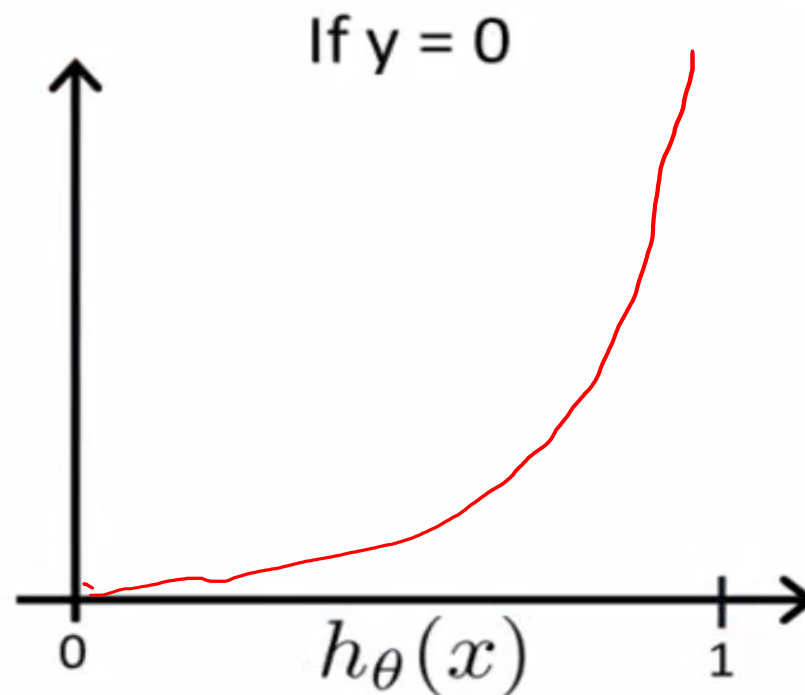
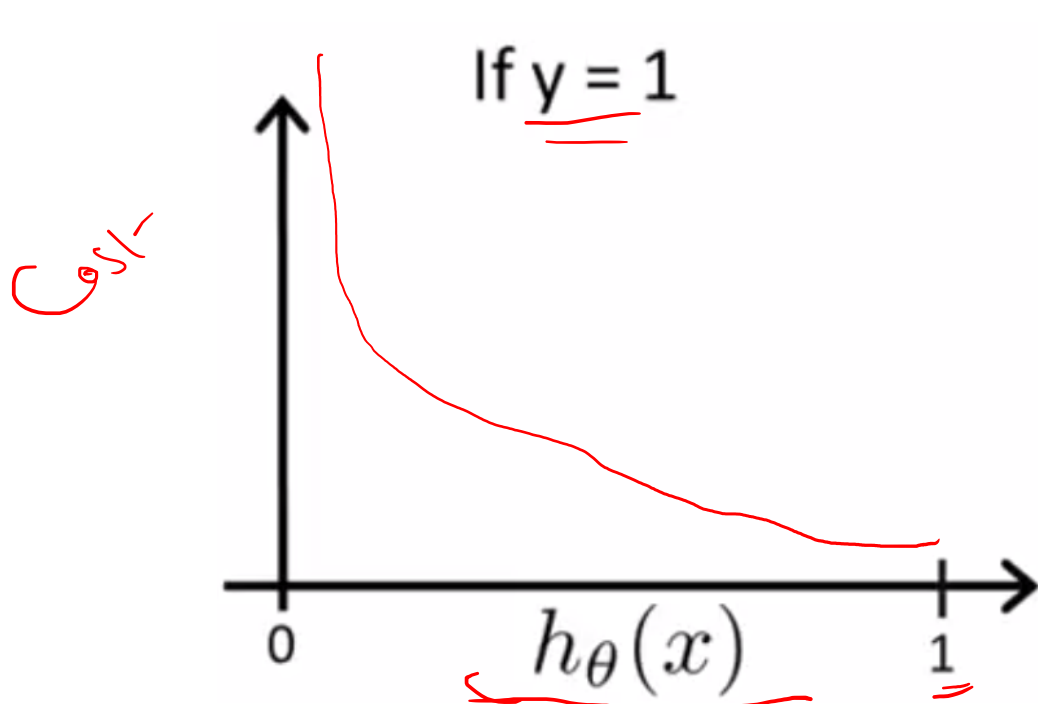
A red arrow points to the fraction $\frac{1}{m}$, and a red box highlights the term $\text{Cost}(h(x^{(i)}), y^{(i)})$.



Cost Function for Logistic Regression – Binary Cross Entropy

$$Cost(h(x), y) = \begin{cases} -\log(h(x)) & \text{if } y = 1 \\ -\log(1 - h(x)) & \text{if } y = 0 \end{cases}$$

Handwritten notes: A red arrow points to the first case, another to the second. A checkmark is next to 'if y = 1'. A red 'x' is next to the first case.



Binary Cross Entropy Loss

$$Cost(h(x), y) = \begin{cases} -\log(h(x)) & \text{if } y = 1 \\ -\log(1 - h(x)) & \text{if } y = 0 \end{cases}$$

$$J(\theta) = \frac{1}{m} \sum_{i=1}^m Cost(h(x^{(i)}), y^{(i)})$$

$$J(\theta) = -\frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \log h(x^{(i)}) + (1 - y^{(i)}) \log(1 - h(x^{(i)})) \right]$$

Finding the Parameter Values – Gradient Descent

$$J(\theta) = -\frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \log h(x^{(i)}) + (1 - y^{(i)}) \log(1 - h(x^{(i)})) \right]$$

- Gradient Descent

Repeat until convergence {

$$\theta_j = \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

}

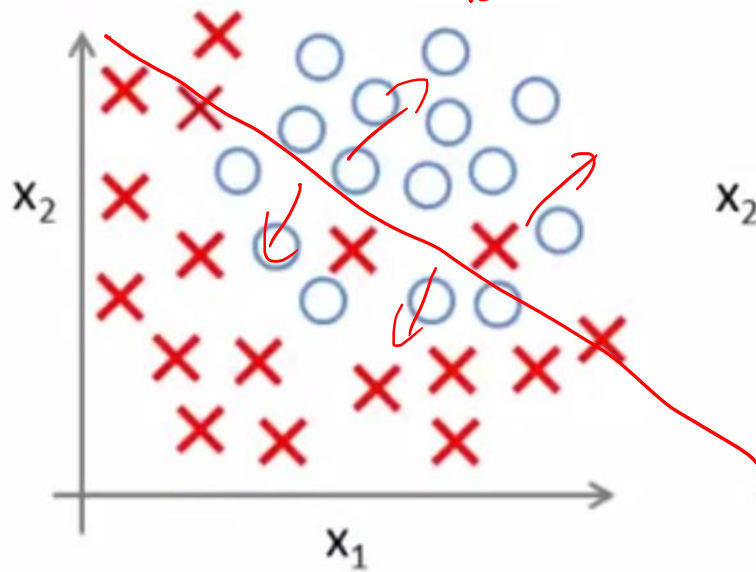
After taking derivative:

Repeat until convergence {

$$\theta_j = \theta_j - \alpha \sum_{i=1}^m h(x^{(i)}) - y^{(i)} x_j^{(i)}$$

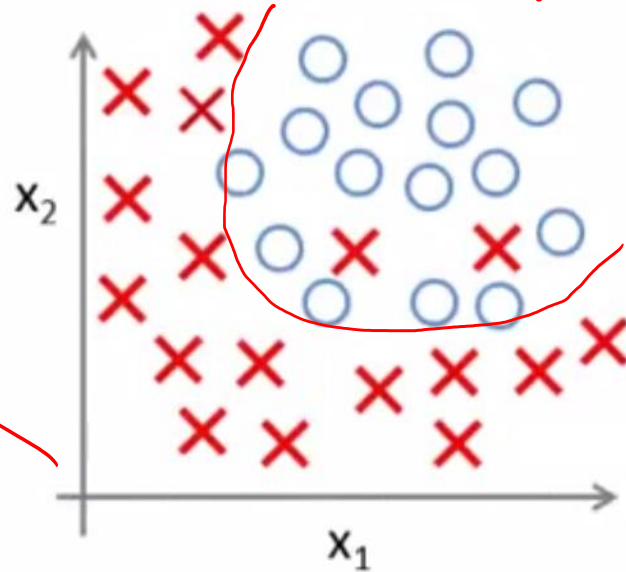
}

Overfitting in Logistic Regression

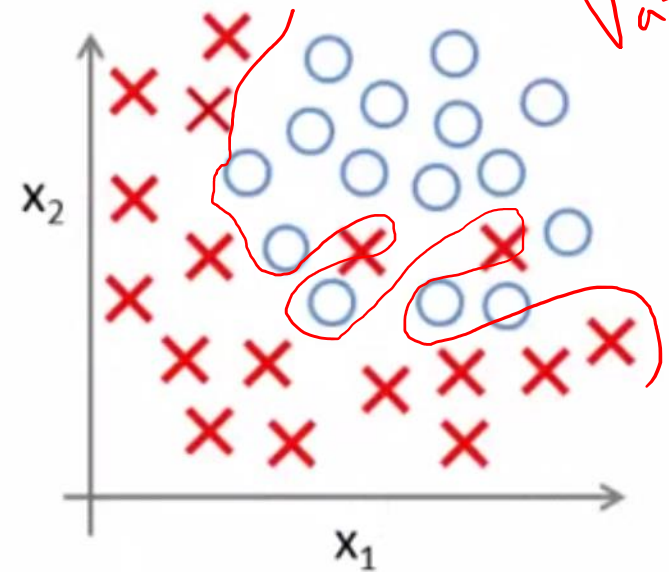


$$h_{\theta}(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$$

(g = sigmoid function)



$$g(\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1^2 + \theta_4 x_2^2 + \theta_5 x_1 x_2)$$



$$g(\theta_0 + \theta_1 x_1 + \theta_2 x_1^2 + \theta_3 x_1^2 x_2 + \theta_4 x_1^2 x_2^2 + \theta_5 x_1^2 x_2^3 + \theta_6 x_1^3 x_2 + \dots)$$