

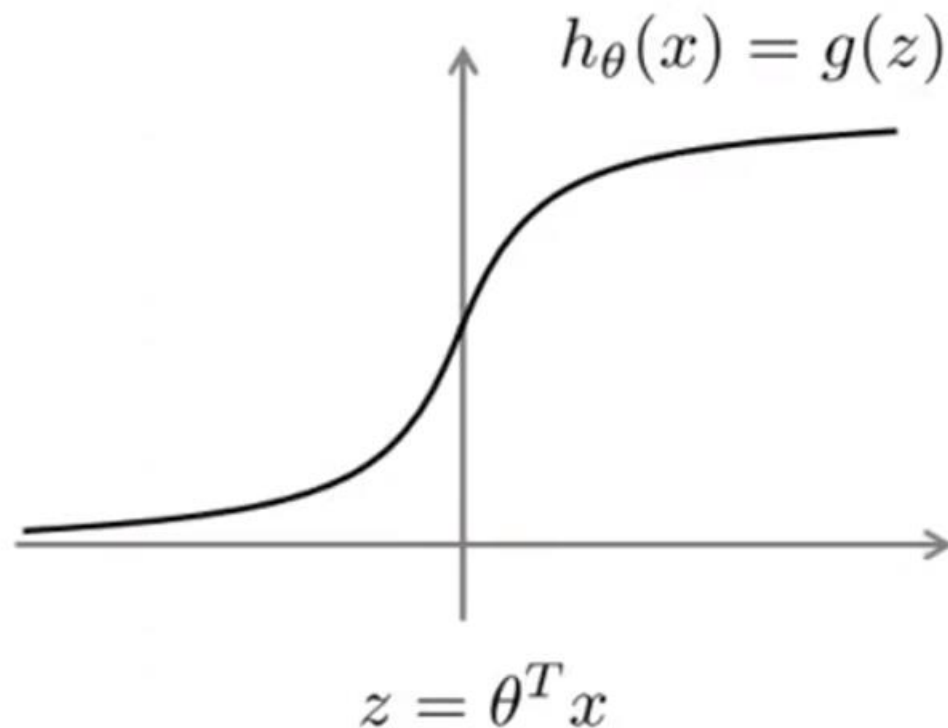
Optimization Objective

Large Margin Classification

Support Vector Machines

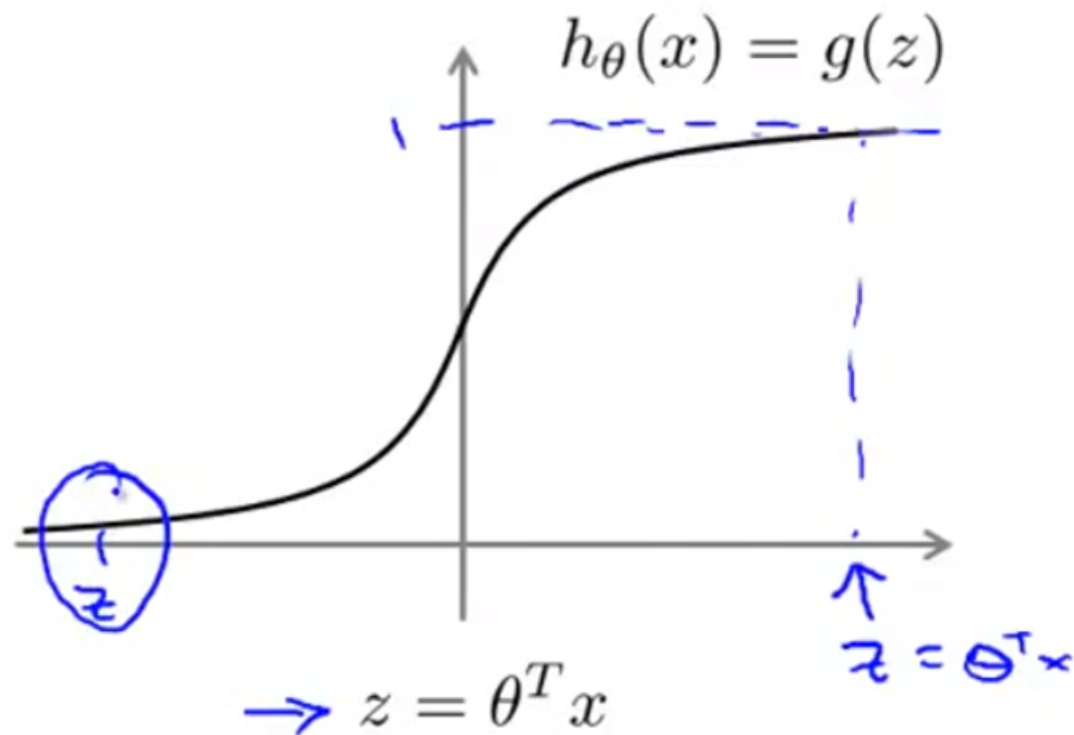
Alternative view of logistic regression

$$h_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}}$$



Alternative view of logistic regression

$$\rightarrow h_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}}$$



If $y = 1$, we want $h_{\theta}(x) \approx 1$, $\theta^T x \gg 0$
If $y = 0$, we want $h_{\theta}(x) \approx 0$, $\theta^T x \ll 0$

Alternative view of logistic regression

(x, y)

Cost of example: $-(y \log h_{\theta}(x) + (1 - y) \log(1 - h_{\theta}(x))) \leftarrow$

$$= -y \log \frac{1}{1 + e^{-\theta^T x}} - (1 - y) \log \left(1 - \frac{1}{1 + e^{-\theta^T x}}\right)$$

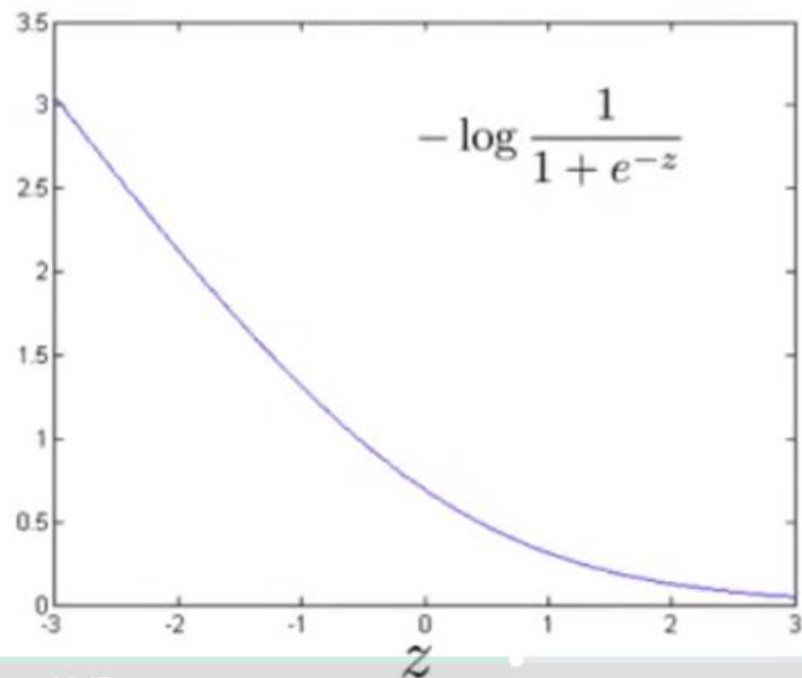
Alternative view of logistic regression

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If $y = 1$ (want $\theta^T x \gg 0$):



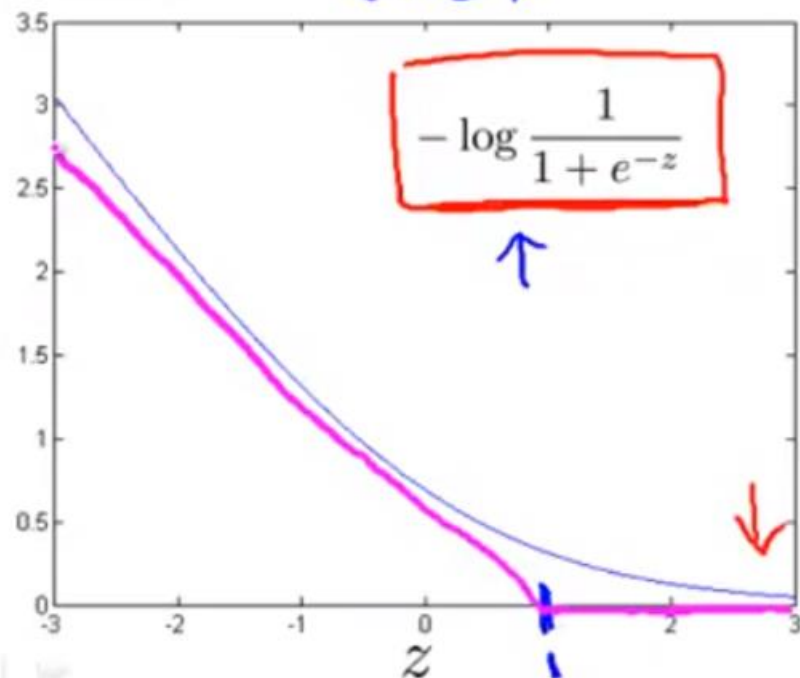
Alternative view of logistic regression

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If $y = 1$ (want $\theta^T x \gg 0$):

$$z = \theta^T x$$



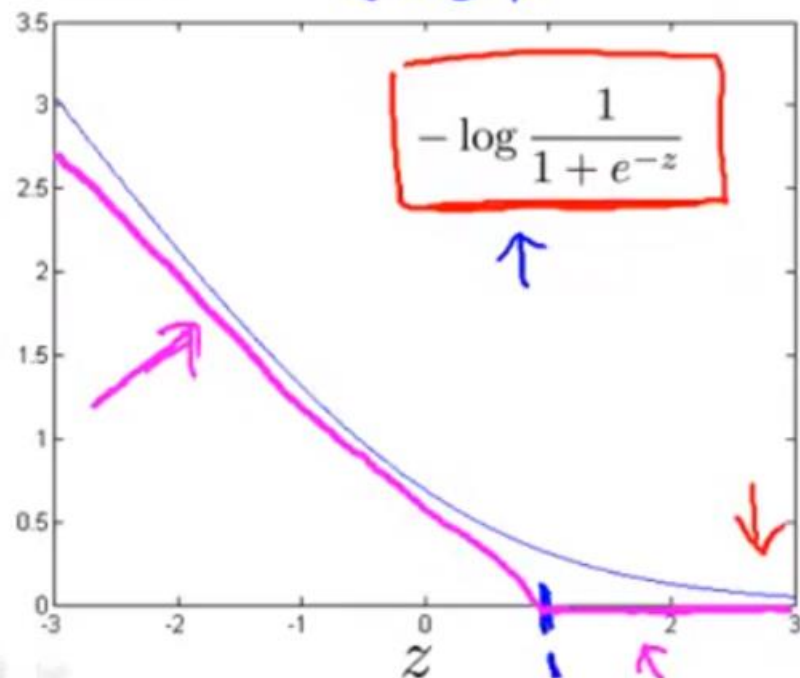
Alternative view of logistic regression

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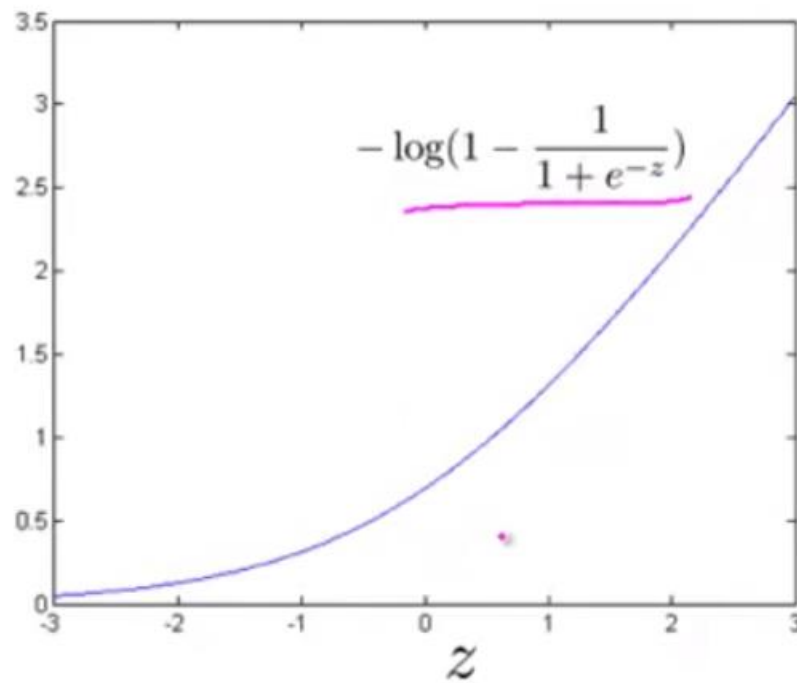
$$= -y \log \frac{1}{1 + e^{-\theta^T x}} - (1 - y) \log \left(1 - \frac{1}{1 + e^{-\theta^T x}}\right)$$

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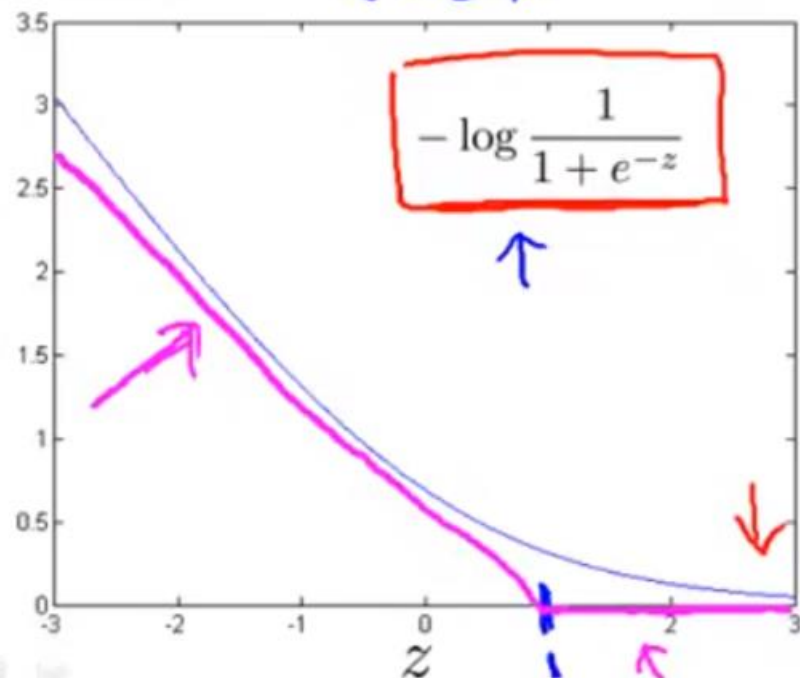
Alternative view of logistic regression

Cost of example: $-(y \log h_{\theta}(x) + (1 - y) \log(1 - h_{\theta}(x)))$ \leftarrow

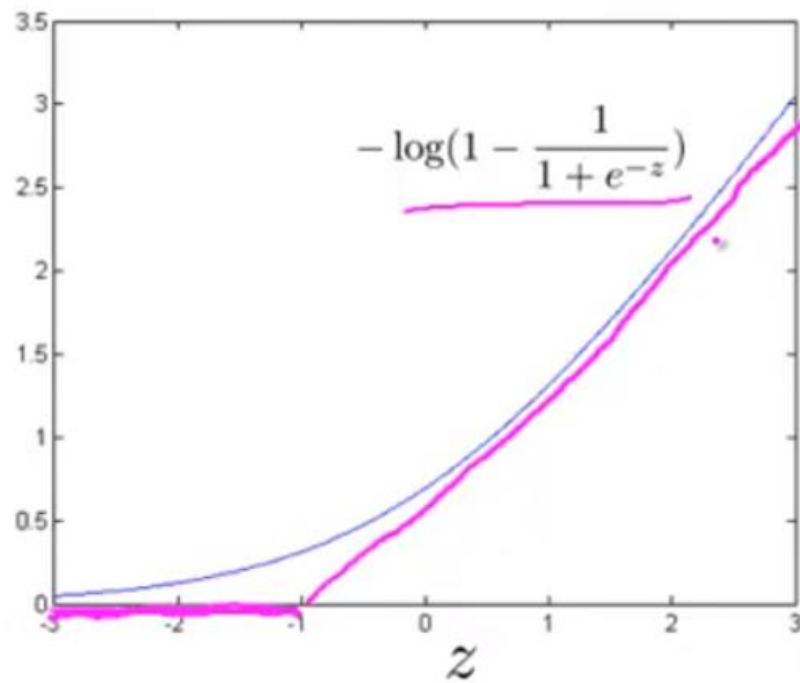
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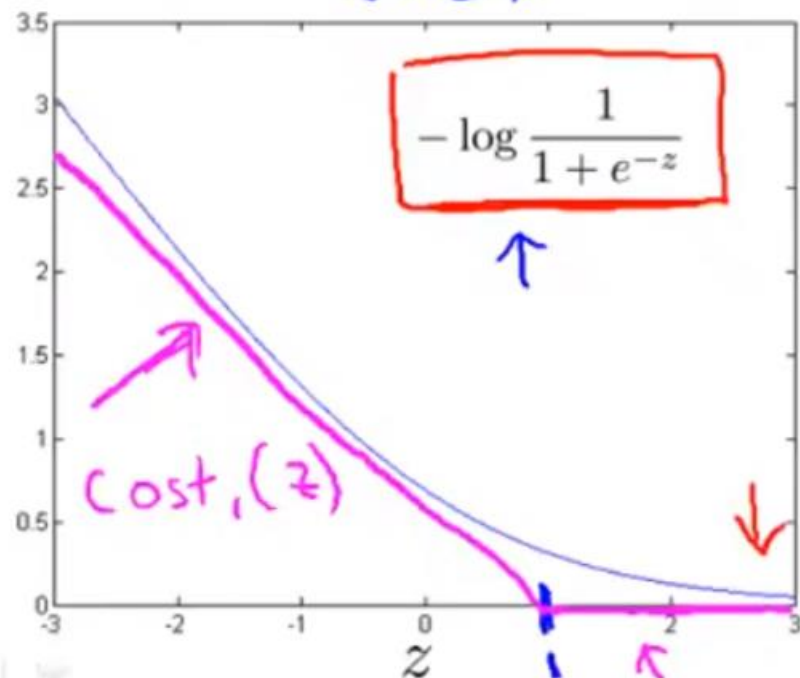
Alternative view of logistic regression

Cost of example: $-(y \log h_{\theta}(x) + (1 - y) \log(1 - h_{\theta}(x)))$ \leftarrow

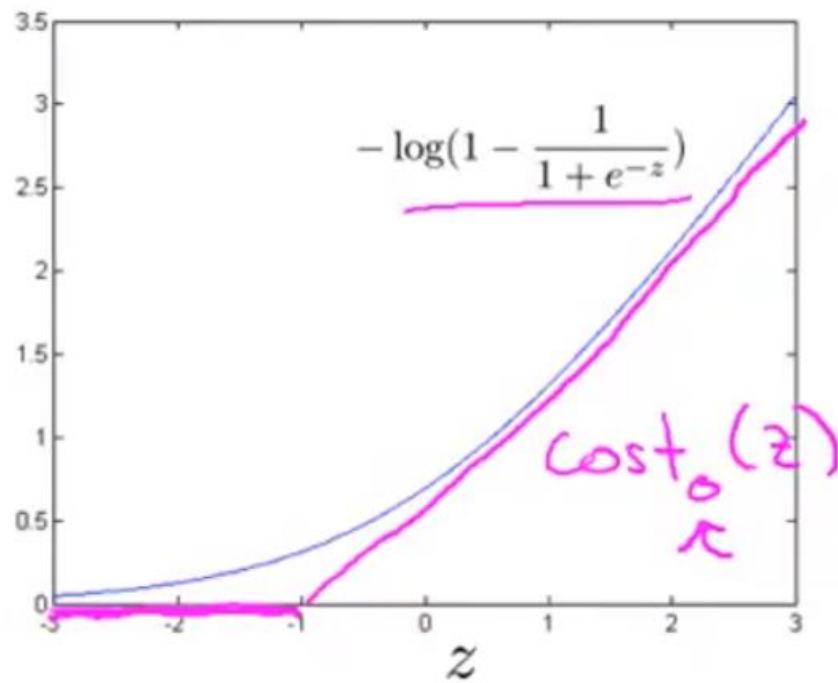
$$= -y \log \frac{1}{1 + e^{-\theta^T x}} - (1 - y) \log \left(1 - \frac{1}{1 + e^{-\theta^T x}}\right)$$

If $y = 1$ (want $\theta^T x \gg 0$):

$$z = \theta^T x$$

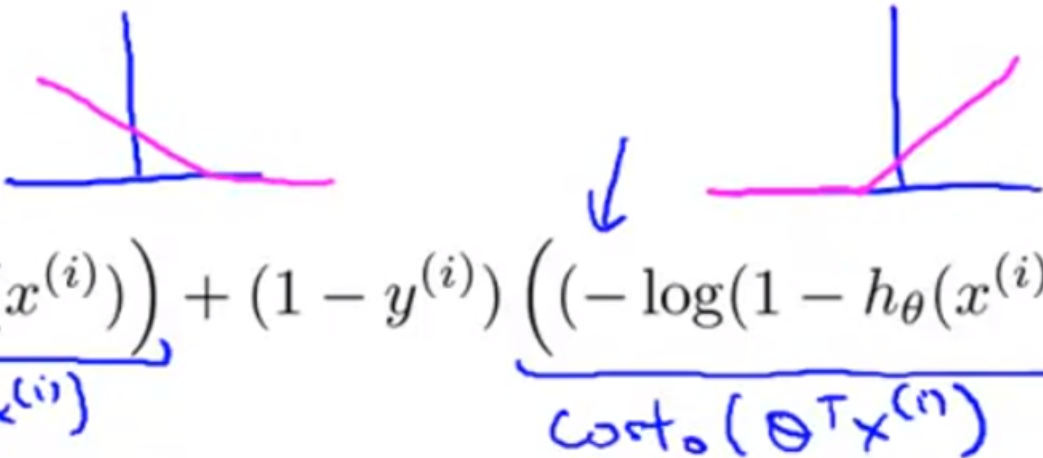


If $y = 0$ (want $\theta^T x \ll 0$):



Support vector machine

Logistic regression:


$$\min_{\theta} \frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \underbrace{\left(-\log h_{\theta}(x^{(i)}) \right)}_{\text{cost}_1(\theta^T x^{(i)})} + (1 - y^{(i)}) \underbrace{\left(-\log(1 - h_{\theta}(x^{(i)})) \right)}_{\text{cost}_0(\theta^T x^{(i)})} \right] + \frac{\lambda}{2m} \sum_{j=1}^n \theta_j^2$$


Support vector machine:

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Support vector machine

Logistic regression:



$$\min_{\theta} \frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \underbrace{\left(-\log h_{\theta}(x^{(i)}) \right)}_{\text{cost}_1(\theta^T x^{(i)})} + (1 - y^{(i)}) \underbrace{\left(-\log(1 - h_{\theta}(x^{(i)})) \right)}_{\text{cost}_0(\theta^T x^{(i)})} \right] + \frac{\lambda}{2m} \sum_{j=1}^n \theta_j^2$$

Support vector machine:

$$\min_{\theta} \frac{1}{m} \sum_{i=1}^m y^{(i)} \text{cost}_1(\theta^T x^{(i)}) + (1 - y^{(i)}) \text{cost}_0(\theta^T x^{(i)}) + \frac{\lambda}{2m} \sum_{j=1}^n \theta_j^2$$

Support vector machine

Logistic regression:

$$\min_{\theta} \frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \underbrace{\left(-\log h_{\theta}(x^{(i)}) \right)}_{\text{cost}_1(\theta^T x^{(i)})} + (1 - y^{(i)}) \underbrace{\left(-\log(1 - h_{\theta}(x^{(i)})) \right)}_{\text{cost}_0(\theta^T x^{(i)})} \right] + \frac{\lambda}{2m} \sum_{j=1}^n \theta_j^2$$


Support vector machine:

$$\min_{\theta} \frac{1}{m} C \sum_{i=1}^m y^{(i)} \text{cost}_1(\theta^T x^{(i)}) + (1 - y^{(i)}) \text{cost}_0(\theta^T x^{(i)}) + \frac{1}{2} \sum_{j=1}^n \theta_j^2$$

$$\min_u \frac{(u-5)^2 + 1}{10} \rightarrow u=5$$

$$\min_u 10(u-5)^2 + 10 \rightarrow u=5$$


$$A + \lambda B \leftarrow$$

$$\rightarrow C A + B \leftarrow$$

$$C = \frac{1}{\lambda}$$

Support vector machine

Logistic regression:

$$\min_{\theta} \frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \underbrace{\left(-\log h_{\theta}(x^{(i)}) \right)}_{\text{cost}_1(\theta^T x^{(i)})} + (1 - y^{(i)}) \underbrace{\left(-\log(1 - h_{\theta}(x^{(i)})) \right)}_{\text{cost}_0(\theta^T x^{(i)})} \right] + \frac{\lambda}{2m} \sum_{j=1}^n \theta_j^2$$


Support vector machine:

$$\min_{\theta} \cancel{\frac{1}{m}} C \sum_{i=1}^m y^{(i)} \text{cost}_1(\theta^T x^{(i)}) + (1 - y^{(i)}) \text{cost}_0(\theta^T x^{(i)}) + \cancel{\frac{1}{2m}} \sum_{j=1}^n \theta_j^2$$

$$\min_u \left(\frac{(u-5)^2 + 1}{10} \right) \rightarrow u=5$$

$$\min_u 10(u-5)^2 + 10 \rightarrow u=5$$

$$\begin{aligned} \underline{A} + \underline{\lambda} \underline{B} &\leftarrow \\ \rightarrow C \underline{A} + \underline{B} &\leftarrow \end{aligned}$$

$$\underline{C = \frac{1}{\lambda}}$$

$$\rightarrow \min_{\theta} C \sum_{i=1}^m \left[y^{(i)} \text{cost}_1(\theta^T x^{(i)}) + (1 - y^{(i)}) \text{cost}_0(\theta^T x^{(i)}) \right] + \frac{1}{2} \sum_{j=1}^n \theta_j^2$$

SVM hypothesis

$$\Rightarrow \min_{\theta} C \sum_{i=1}^m \left[y^{(i)} \text{cost}_1(\theta^T x^{(i)}) + (1 - y^{(i)}) \text{cost}_0(\theta^T x^{(i)}) \right] + \frac{1}{2} \sum_{j=1}^n \theta_j^2$$

Hypothesis:

$$h_{\theta}(x) = \begin{cases} 1 & \text{if } \theta^T x \geq 0 \\ 0 & \text{otherwise} \end{cases}$$