

# LOGISTIC REGRESSION

# Classification

## Two-class (binary) classification problem

$y : \{0,1\}$

0: negative class

1: positive class

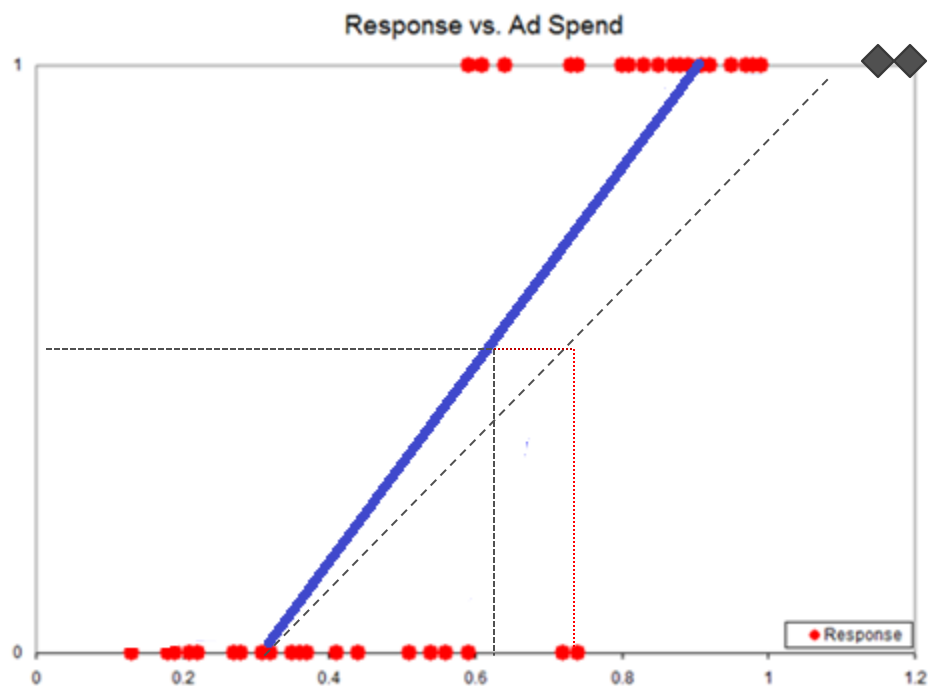
Example: Yes/No; Benign/Malignant ; Click/No click

## Multi-class classification problem

$y:\{0,1,2,\dots,n\}$

Example: Grades (A, B, C); color (red, blue, green)

# Two Class Classification



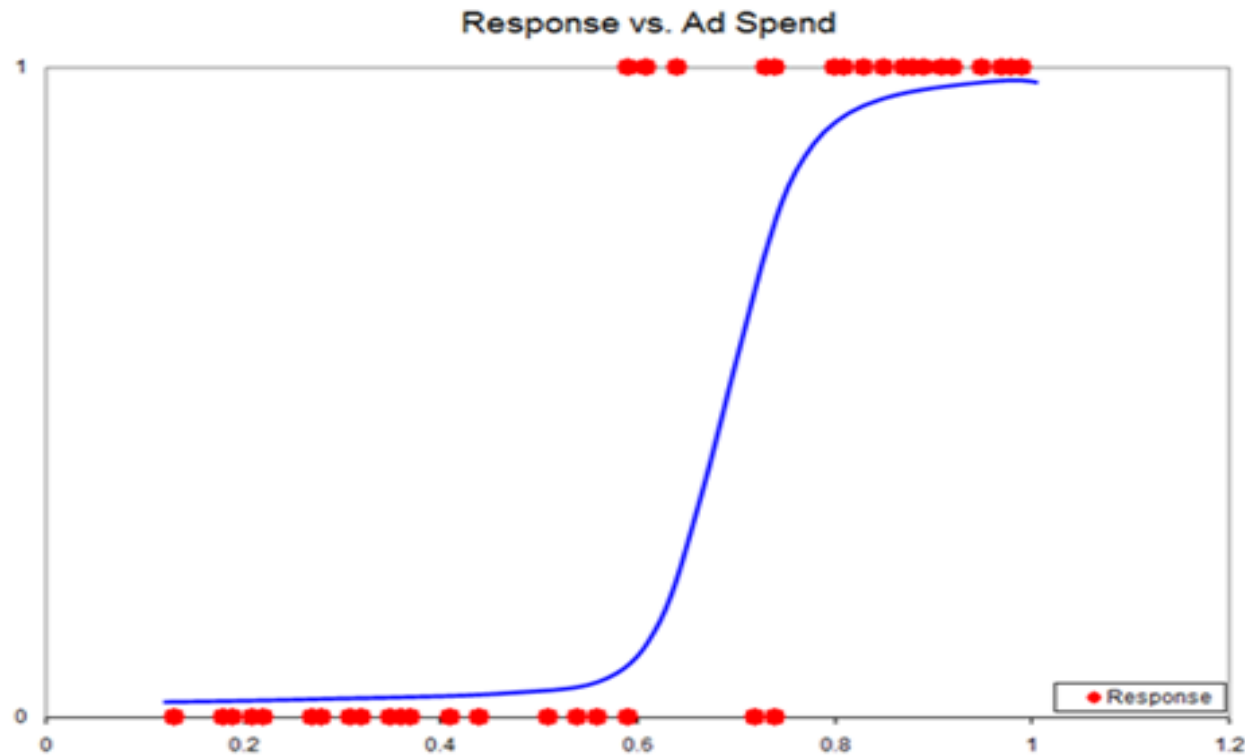
Classification:  $y = 0$  or  $y = 1$

Decision rules:  $h_{\theta}(x) \geq 0.5; y = 1$   
 $h_{\theta}(x) < 0.5; y = 0$

If we use linear regression on classification problem, we may observe

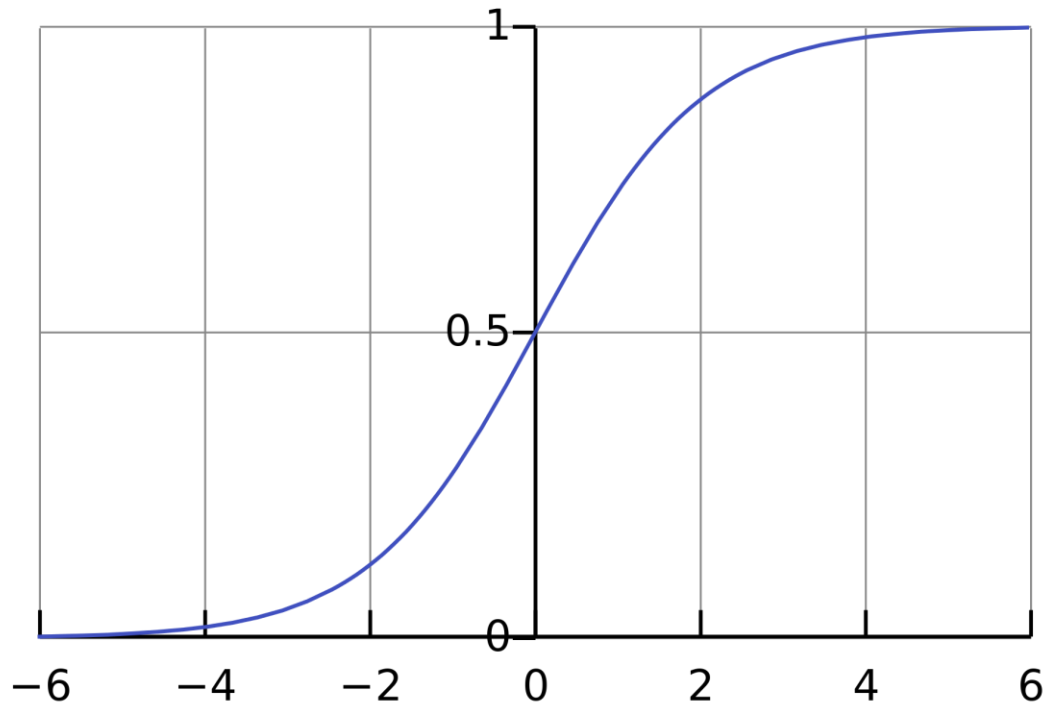
- Shift the decision rule line
- $h_{\theta}(x)$  can be  $> 1$  or  $< 0$

# Logistic Regression



More reasonable function  
use for two-class  
classification problem.

# Sigmoid Function



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

## Hypothesis interpretation

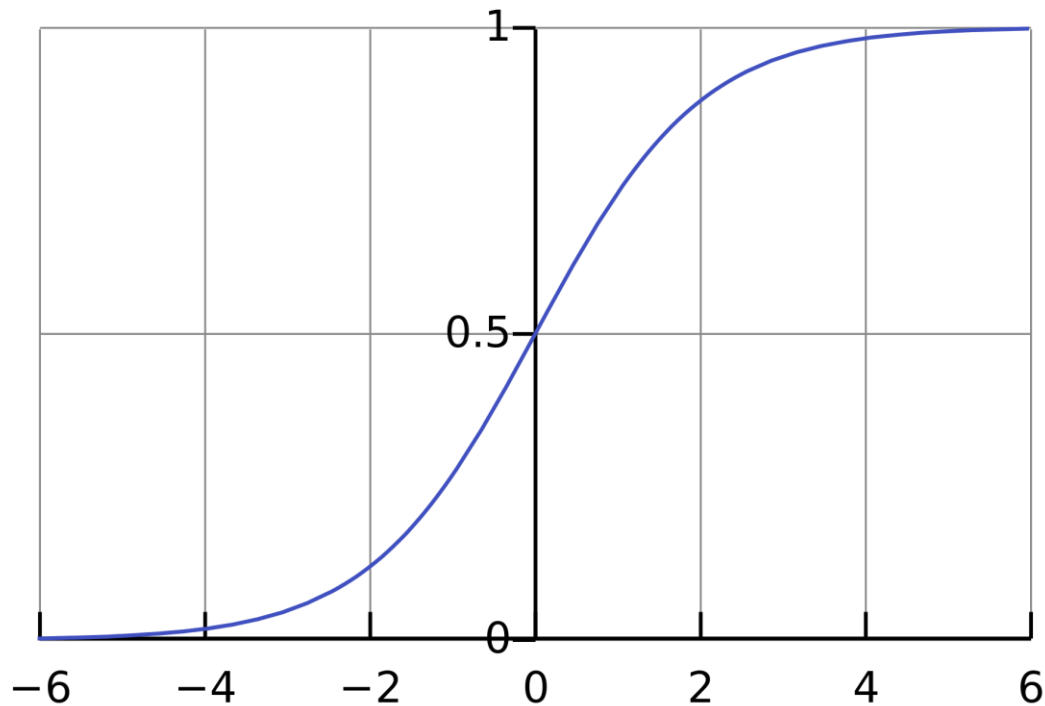
Estimated probability that  $y=1$  on  $x$  input

$$P(y=1 | x; \theta_j)$$

Because probabilities should sum to 1

$$P(y=0 | x; \theta_j) = 1 - P(y=1 | x; \theta_j)$$

# Sigmoid Function



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

$$y = 1 \text{ if } h_{\theta}(x) \geq 0.5$$

$$y = 0 \text{ if } h_{\theta}(x) < 0.5$$

0 asymptote for  $x \rightarrow -\infty$

1 asymptote for  $x \rightarrow \infty$

# Cost Function for Logistic Regression

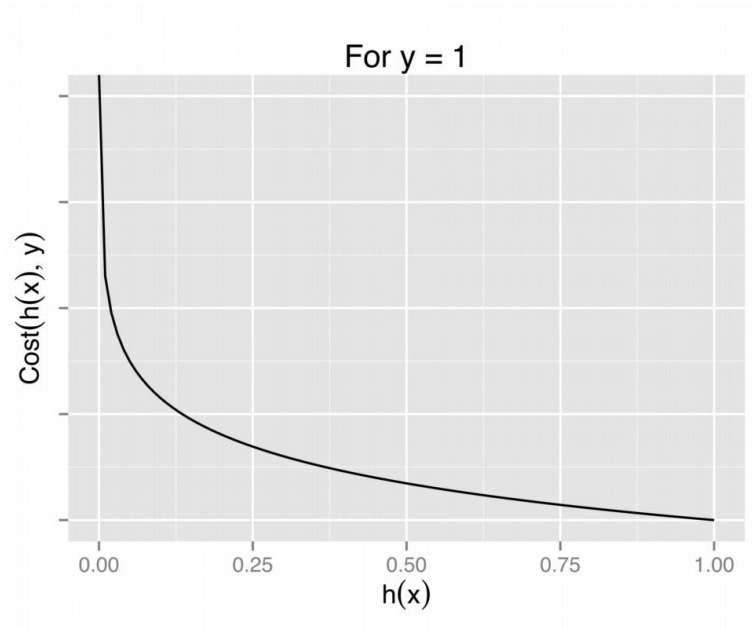
## Average cost function

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

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

# Cost Function for Logistic Regression

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



If we predict  $h_{\theta}(x) = 1$  and  $y = 1$

Cost function  $\longrightarrow$  zero

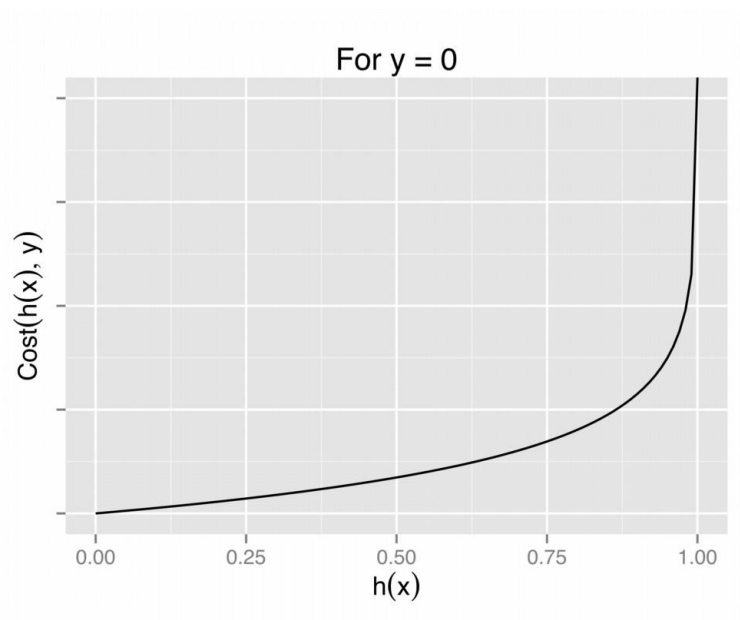
If we predict  $h_{\theta}(x) = 0$  and  $y = 1$

Cost function  $\longrightarrow -\infty$



# Cost Function for Logistic Regression

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



If we predict  $h_{\theta}(x) = 0$  and  $y = 0$

Cost function  $\longrightarrow$  zero

If we predict  $h_{\theta}(x) = 1$  and  $y = 0$

Cost function  $\longrightarrow \infty$

# Cost Function for logistic regression

## Average cost function

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

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

Simplified cost function, given we only have either  $y=0$  or  $y=1$

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

# Cost Function: Recap

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

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

Parameters:  $\theta_j$

Goal:  $\underset{\theta}{\operatorname{argmin}} J(\theta)$

# Gradient Descent Algorithm

- We want to learn the values of  $\theta$  that minimize  $J(\theta)$
- Use a search algorithm that starts with an initial guess for  $\theta$  and then changes  $\theta$  to make  $J(\theta)$  smaller
- Gradient descent starts with some initial  $\theta$  and then performs an update for each value  $\theta_j$

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

# Minimizing The Cost Function $J(\theta)$

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

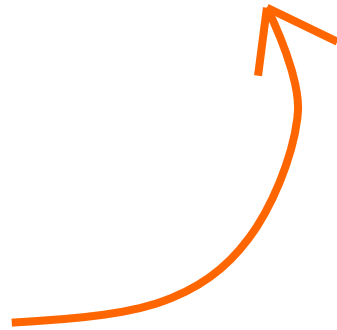


After derivative

$$\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_j^{(i)}$$

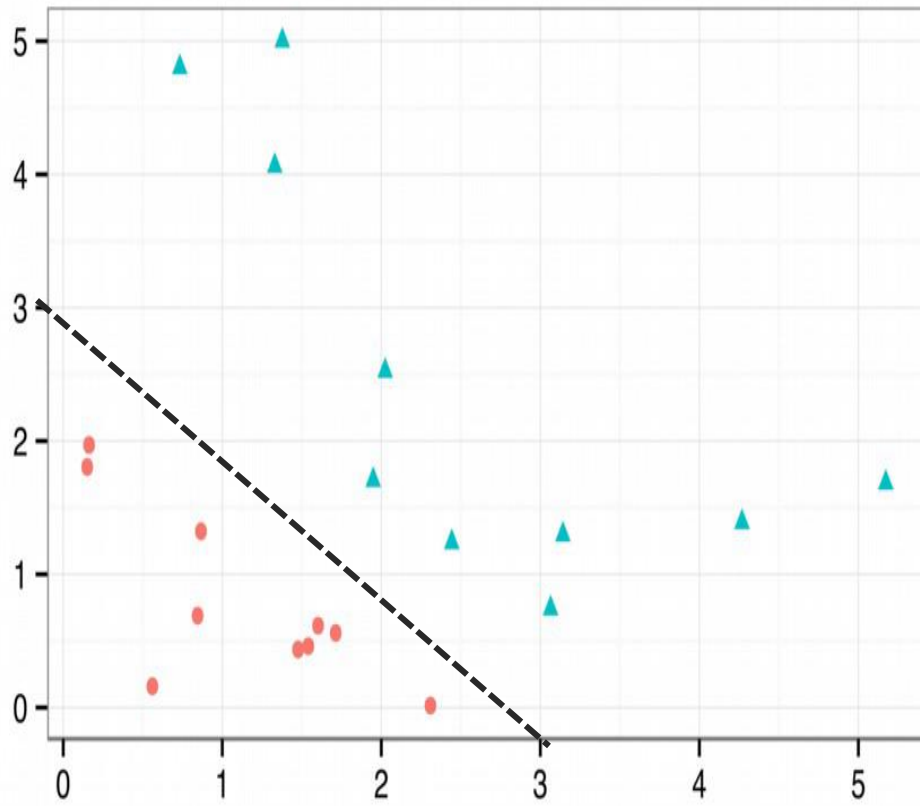


$$\theta := \begin{bmatrix} tmp_0 \\ \vdots \\ tmp_n \end{bmatrix}$$



Repeat until converged

# Decision Boundary: Linear



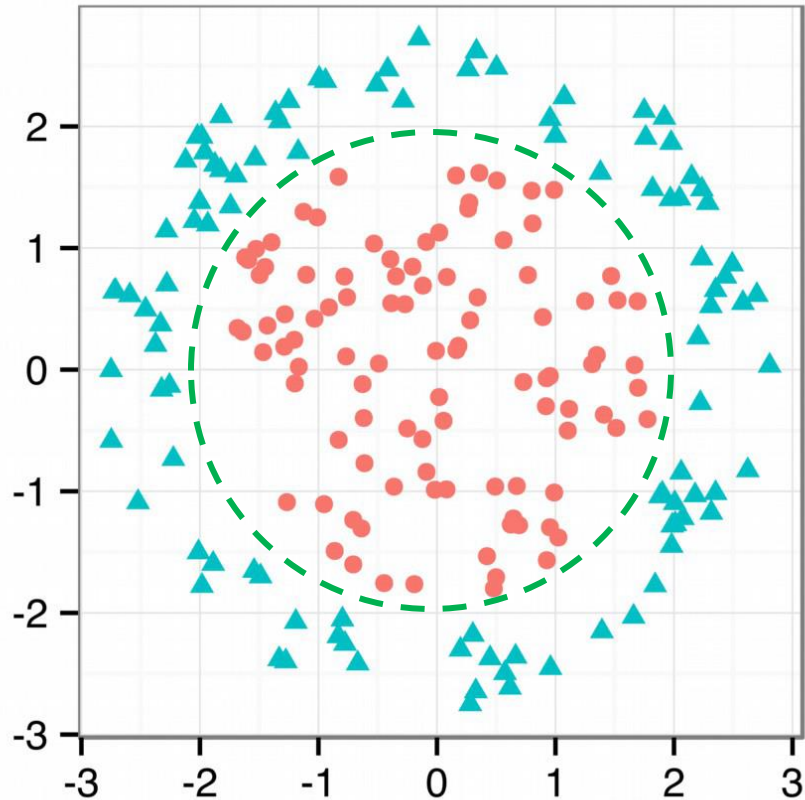
If  $h_{\theta}(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$

And  $\theta = \begin{bmatrix} -3 \\ 1 \\ 1 \end{bmatrix}$

Prediction  $y = 1$  whenever

$$\begin{aligned} \theta^T x &\geq 0 \\ \Leftrightarrow -3 + x_1 + x_2 &\geq 0 \\ \Leftrightarrow x_1 + x_2 &\geq 3 \end{aligned}$$

# Decision Boundary: Non-Linear



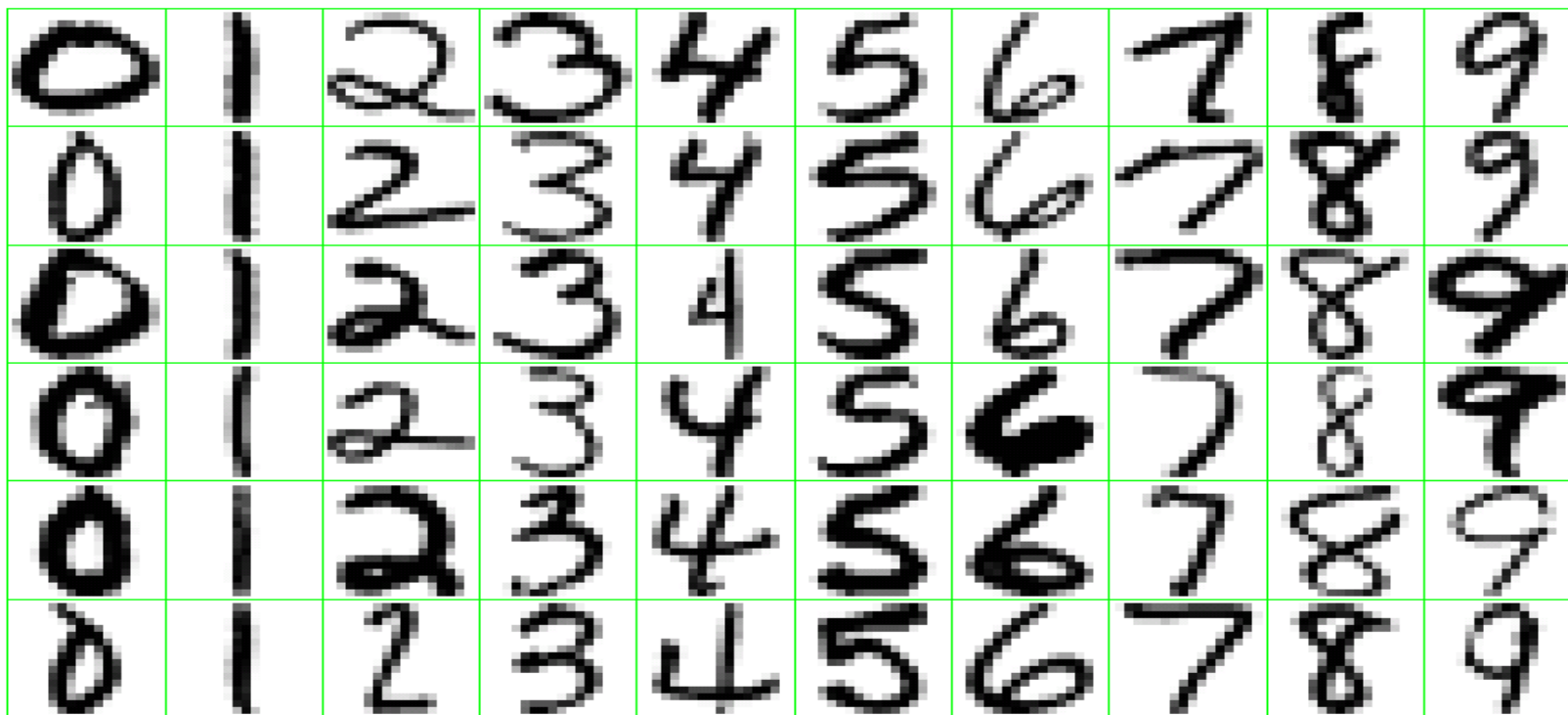
If  $h_{\theta}(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1^2 + \theta_4 x_2^2)$

And  $\theta = [-2 \ 0 \ 0 \ 1 \ 1]^T$

Prediction  $y = 1$  whenever

$$x_1^2 + x_2^2 \geq 2$$

# Example: Handwritten Digit Recognition





# Questions?