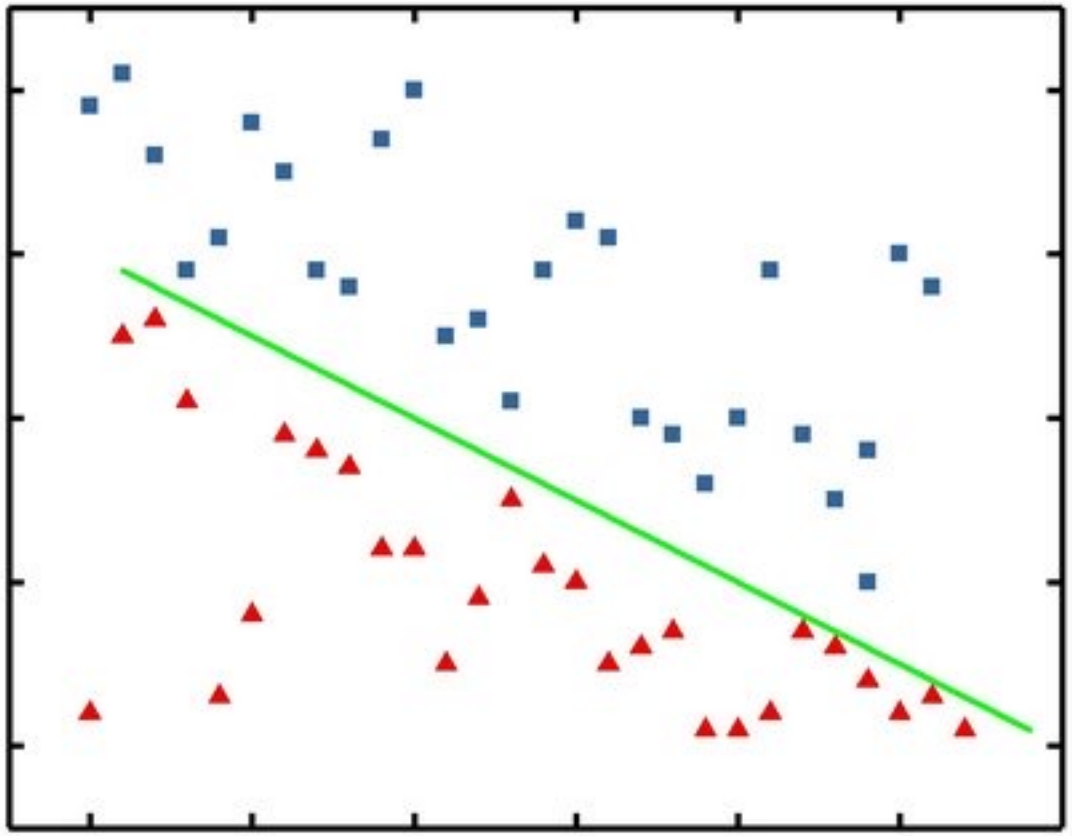
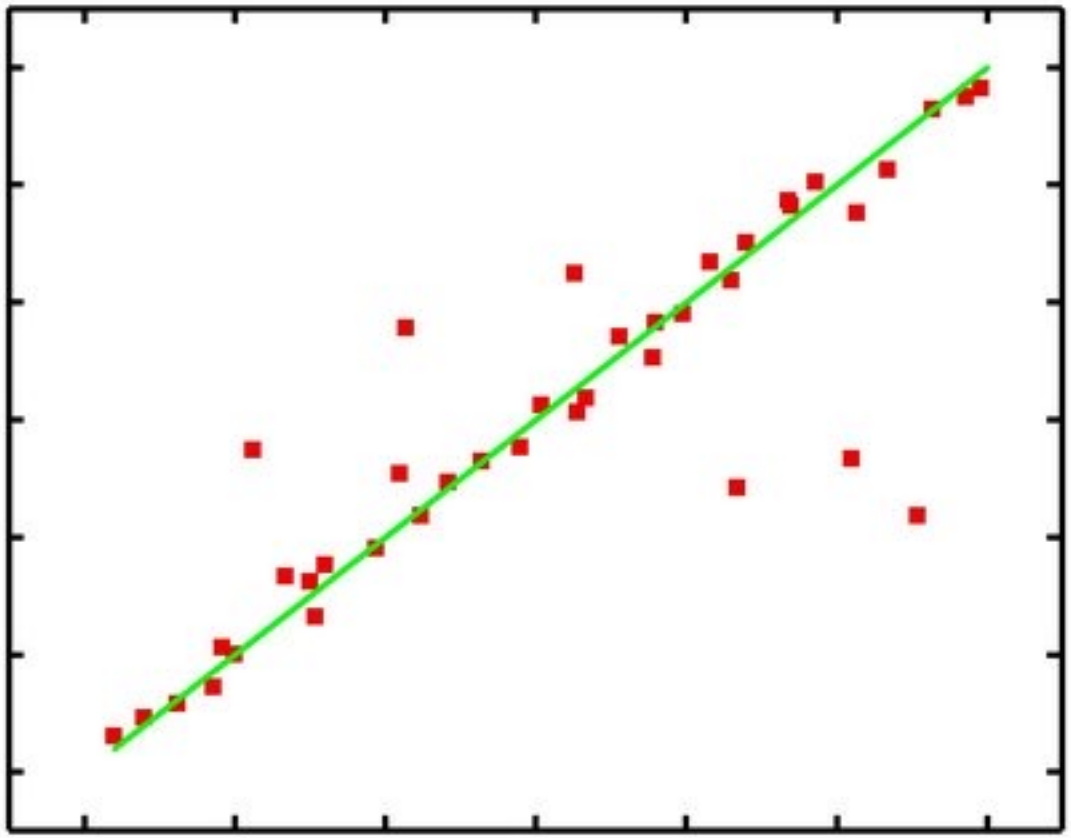
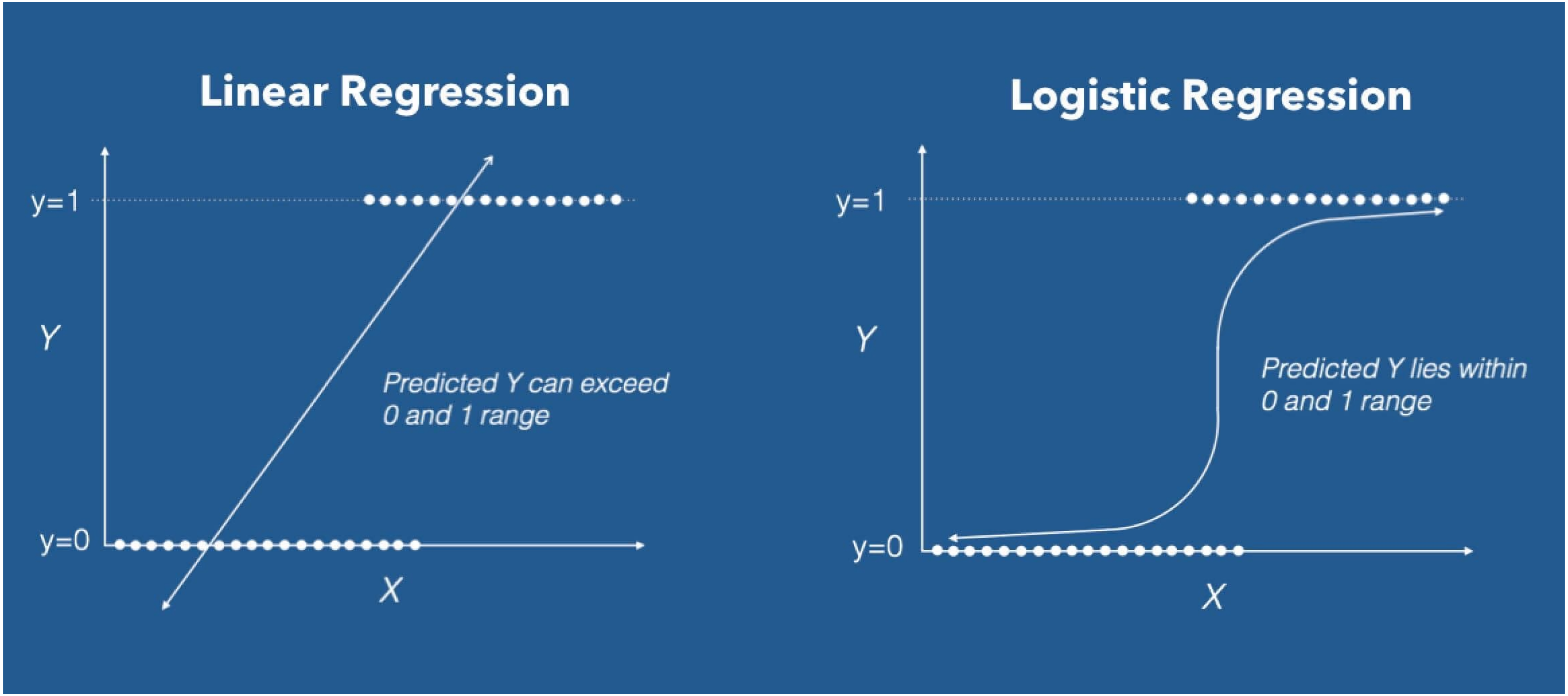
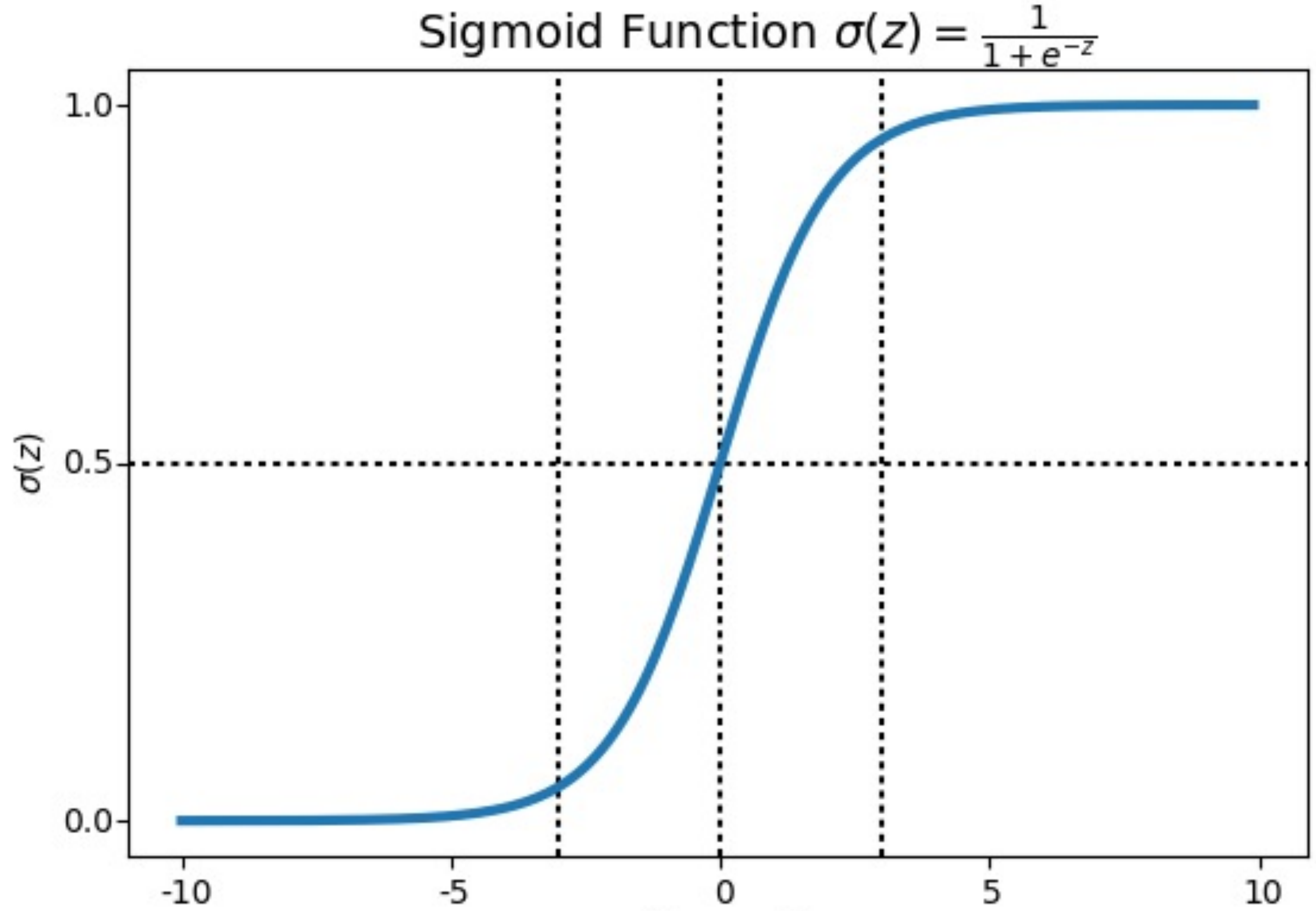


(a) Logistic Regression



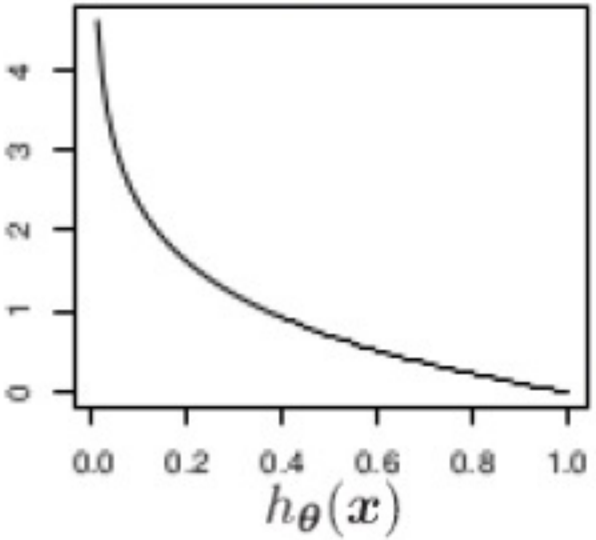
(b) Linear Regression


Linear Regression
y=1
Y
Predicted Y can exceed
0 and 1 range
y=0
X
Logistic Regression
y=1
Y
Predicted Y lies within
0 and 1 range
y=0
X


Sigmoid Function $\sigma(z) = \frac{1}{1+e^{-z}}$
$\sigma(z)$
1.0
0.5
0.0
-10
-5
0
5
10

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

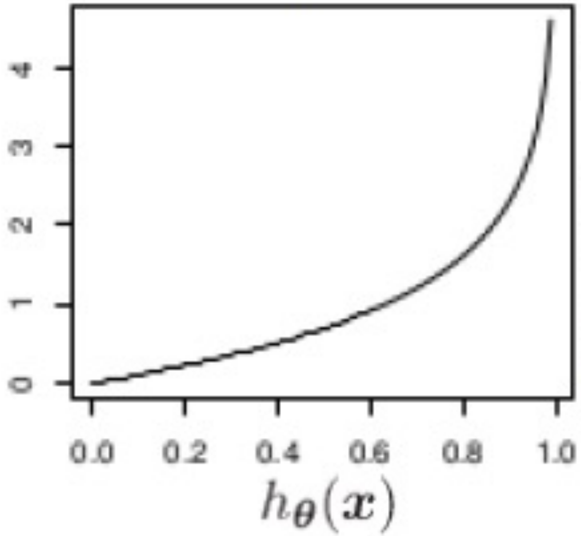
if $\ y = 1$



if $h_{\boldsymbol{\theta}}(\boldsymbol{x}) = 1$
then cost $= 0$

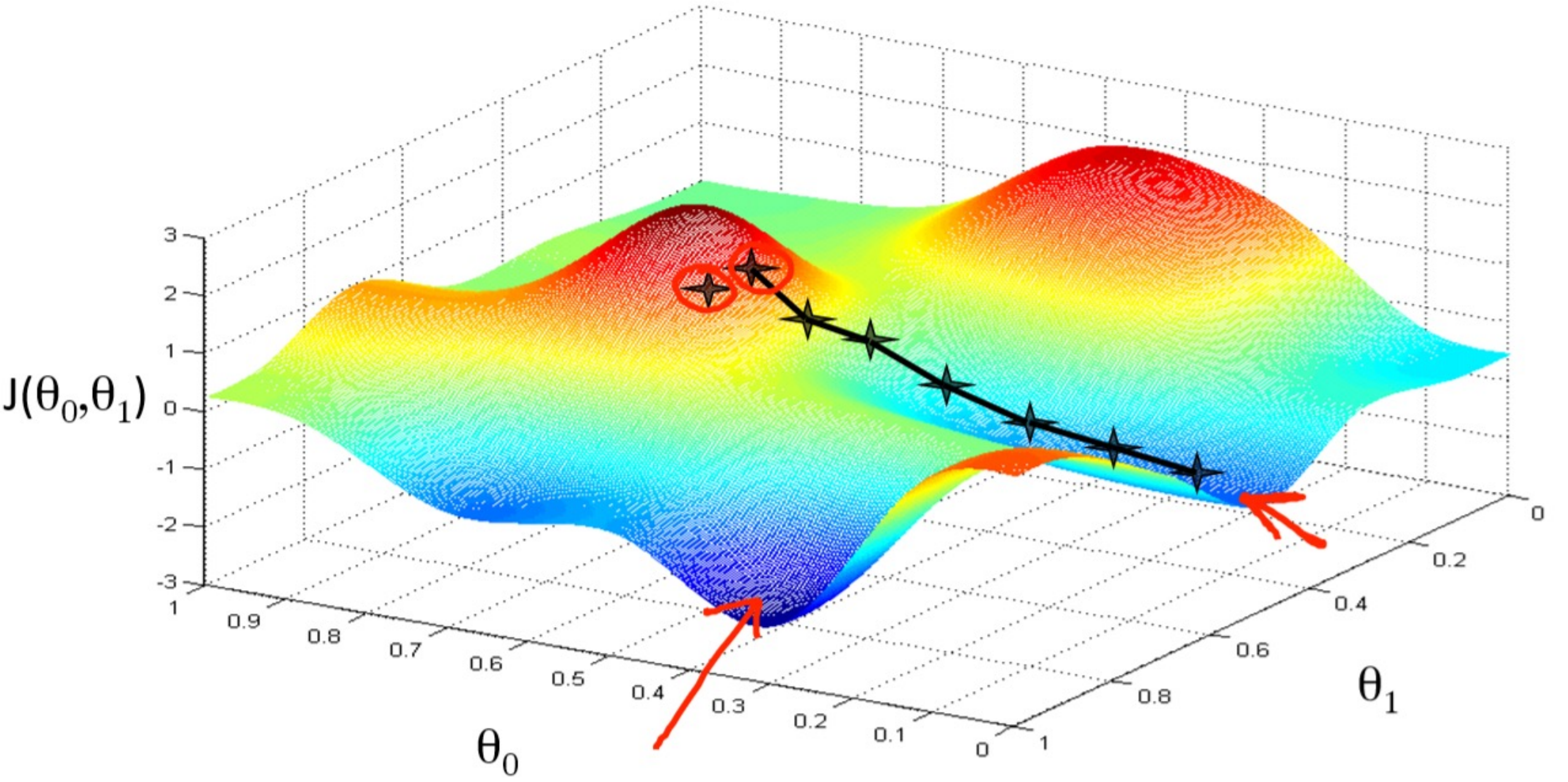
if $h_{\boldsymbol{\theta}}(\boldsymbol{x}) \to 0$
then cost $\to \infty$
predicted
$\text{prob}(y = 1 \mid \boldsymbol{x}; \boldsymbol{\theta}) = 0$
but $y = 1$

if $\ y = 0$



if $h_{\boldsymbol{\theta}}(\boldsymbol{x}) = 0$
then cost $= 0$

if $h_{\boldsymbol{\theta}}(\boldsymbol{x}) \to 1$
then cost $\to \infty$
predicted
$\text{prob}(y = 0 \mid \boldsymbol{x}; \boldsymbol{\theta}) = 0$
but $y = 0$



$J(\theta_0,\theta_1)$
3
2
1
0
-1
-2
-3
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
θ_0
0
0.2
0.4
0.6
0.8
1
θ_1

ENTROPY

- Let X be a random variable taking finite number of values $x_1, x_2, \dots, x_n$
- Let X have a probability mass function $p_i \equiv \mathrm{P}(X = x_i)$
- Define function of X:

$$g(x) \equiv -\log_2 \mathrm{P}(X = x)$$

- Note that $g(x_i) = -\log_2 p_i = \log_2 \frac{1}{p_i}$
- Shannon's **entropy** of X is defined as:

$$\mathrm{H}(X) \equiv \mathrm{E}[g(X)] = \sum_{i=1}^{n} g(x_i)\mathrm{P}(X = x_i) = \sum_{i=1}^{n} p_i \log_2 \frac{1}{p_i}$$

- Measure of *uncertainty* of the system's state