

# Logistic Regression

Linear Regression (Reg. Model)

$$\hat{y} = W^T x$$

Cont. Value  $(-\infty, +\infty)$

Car price  $\log(y) = W^T x$

Examples

$$p(\text{churn}) = 0.8$$

$$p(\text{spam}) = 0.2$$

$$p(\text{click}) = 0.6$$

Logistic Regression (clf Model)

$$\hat{y} = \phi(W^T x)$$

limits  $(0, 1)$

class

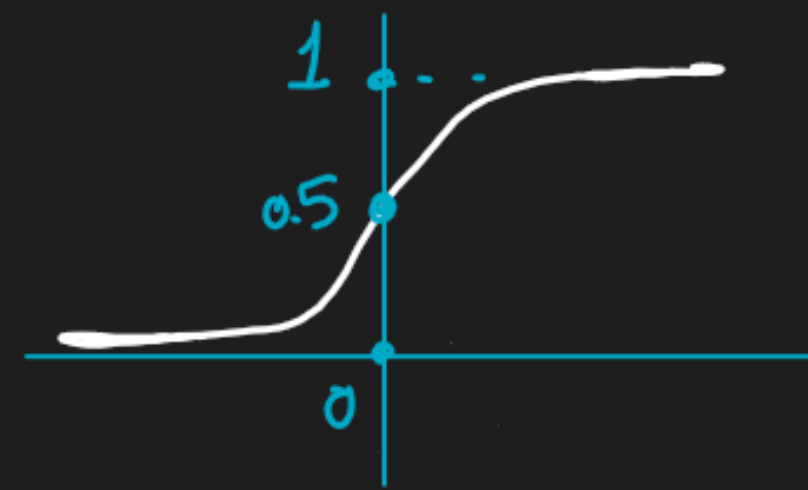
0 1

Binary

Multi 0, 1, 2, 3, ...

Hard clf

Soft + clf



$$\hat{y} = P(\text{class 1})$$

Cont. Value  $(0, 1)$

Soft clf

$$p(\text{churn}) = 0.8$$

$$p(\text{spam}) = 0.2$$

$$p(\text{click}) = 0.6$$

→ Hard clf

threshold  
0.5

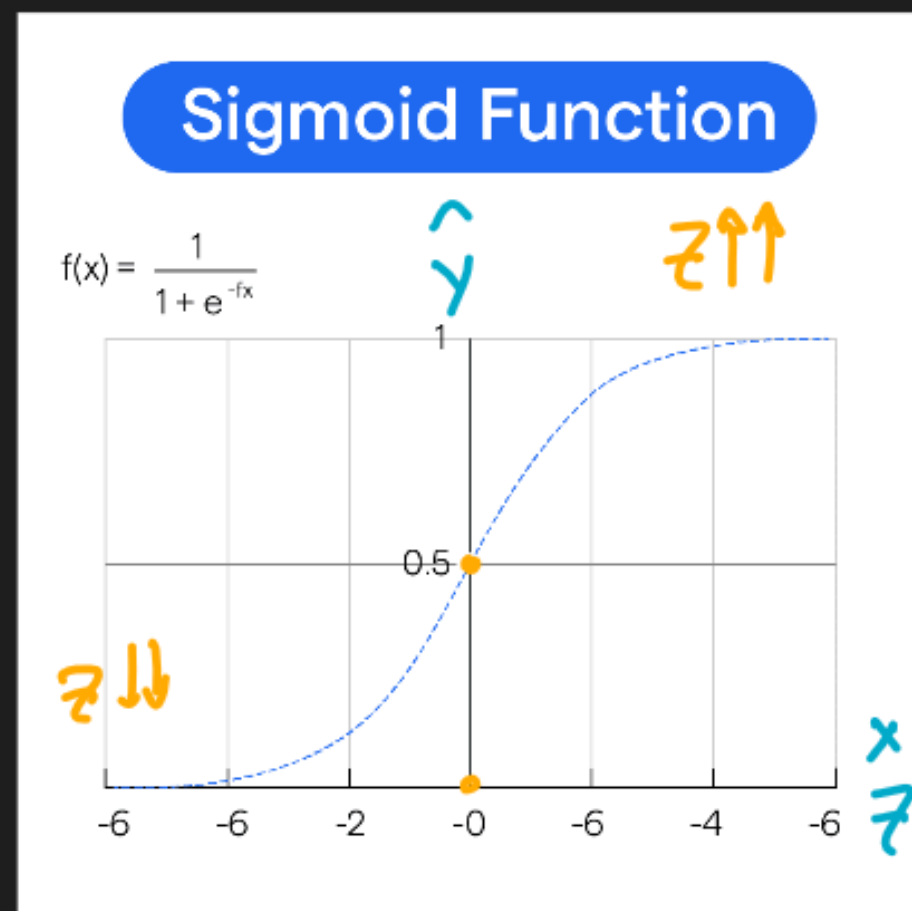
threshold  
0.4

threshold  
0.7

churn (class 1)

Not spam (class 0)

Not click (class 0)



$$\hat{y} = \sigma(\mathbf{w}^T \mathbf{x})$$

Annotations:  $p(\text{class 1})$  (blue),  $\mathbf{z} = \mathbf{w}^T \mathbf{x}$  (orange)

Logistic Regression

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

Limit  $\leftarrow$   
 $-\infty$   
 $\downarrow$   
 $+\infty$

$z \downarrow \downarrow$   
 $-\infty$



$\sigma(z) \downarrow \downarrow$   
 $0$

$z \uparrow \uparrow$   
 $+\infty$



$\sigma(z) \uparrow \uparrow$   
 $1$

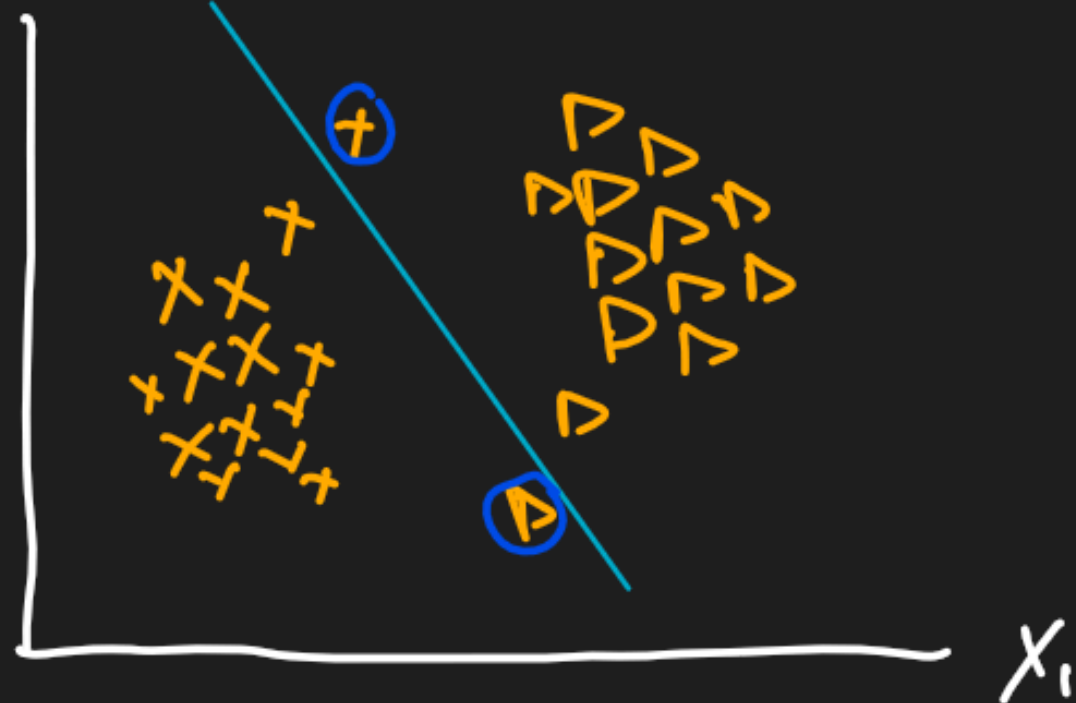
$z = 0$



$\sigma(z) = 0.5$

$$w_1 x_1 + w_2 x_2 = 0$$

$x_2$



Limit  $\leftarrow$   
 $0$

$\downarrow$   
 $1$

(prop)

Decision Boundary

$$w^T x = 0 \rightarrow \sigma(w^T x) = 0.5$$

$$w^T x > 0 \rightarrow \sigma(w^T x) = 1$$

$$w^T x < 0 \rightarrow \sigma(w^T x) = 0$$

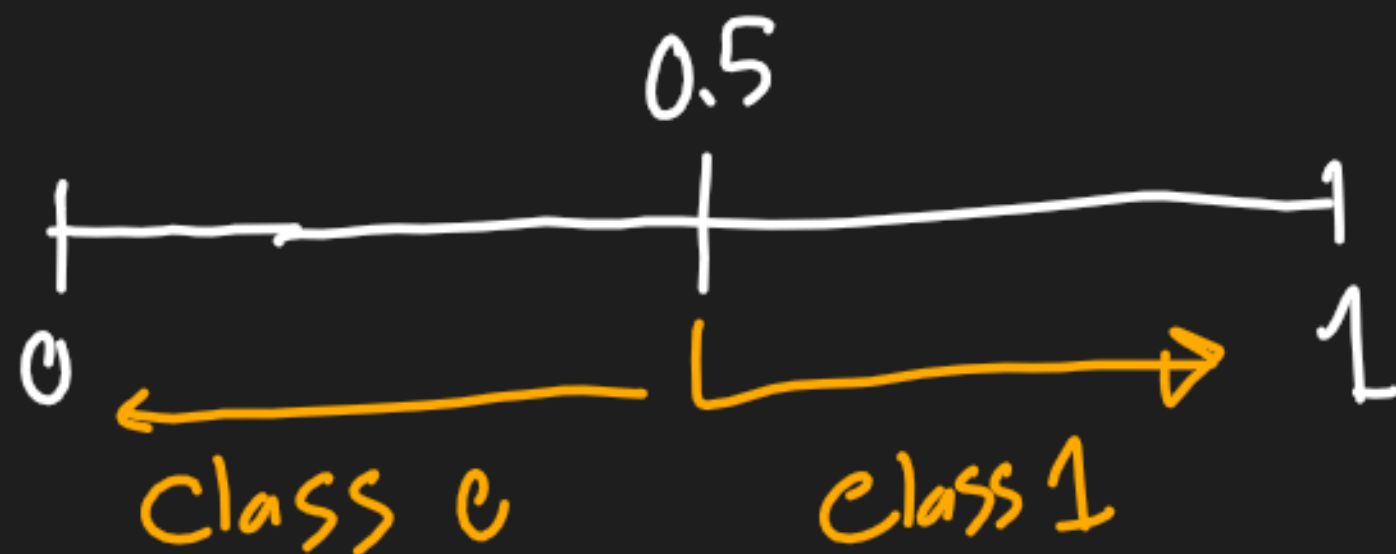
# Logistic Regression

$$y = \sigma(w^T x)$$

$$y = \sigma(w_0 + w_1 x_1 + w_2 x_2 + \dots + w_n x_n)$$

$$y = w^T x \geq 0$$

$$y = w_0 + w_1 x_1 + w_2 x_2 + \dots + w_n x_n \geq 0$$



# Logistic Regression Training

→ Get Weights

$$\underline{y} = \sigma(\underline{w}^T \underline{x})$$

??

Binary CF

	(y) Actual	( $\hat{y}$ ) pred
y=0	0	0
	0	1
y=1	1	0
	1	1

Cost (Error)

↓

↑

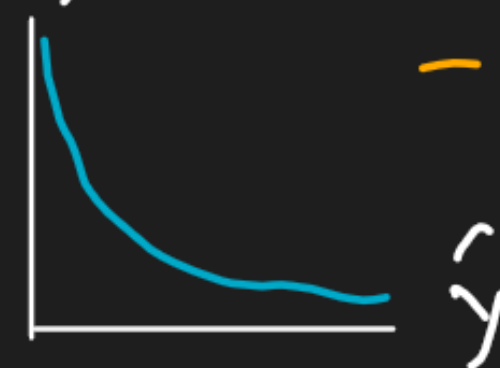
↑

↓

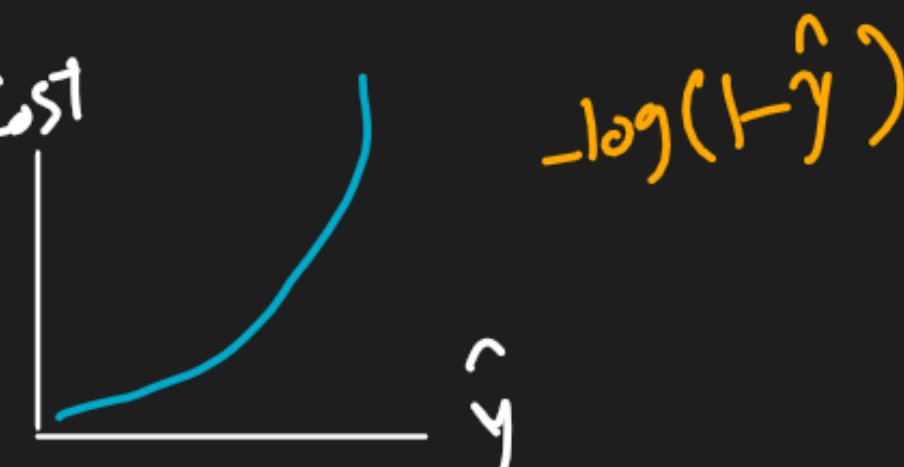
y=1

y=0

Cost



Cost



✓ Define Cost Function (Error)

✓ Optimization

→ Get weights for Min Error

↓  
Misclassification



$$\text{Cost } f_n = \begin{cases} -\log(\hat{y}) & y=1 \\ -\log(1-\hat{y}) & y=0 \end{cases}$$

$$J = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

Binary  
Cross Entropy  
log-loss function

$$J(w) = -\frac{1}{m} \sum_{i=1}^m y^{(i)} \log(\sigma(w^T x^{(i)})) + (1-y^{(i)}) \log(1 - \sigma(w^T x^{(i)}))$$

→ Get weights for  $\text{Min } J$

Linear Reg

$$J = f_1(w)$$

MSE

Log. Reg.

$$J = f_2(w)$$

Cross Entropy

→ Gradient Descent (optimization) → Get Best Weights

1- initialize Random weights

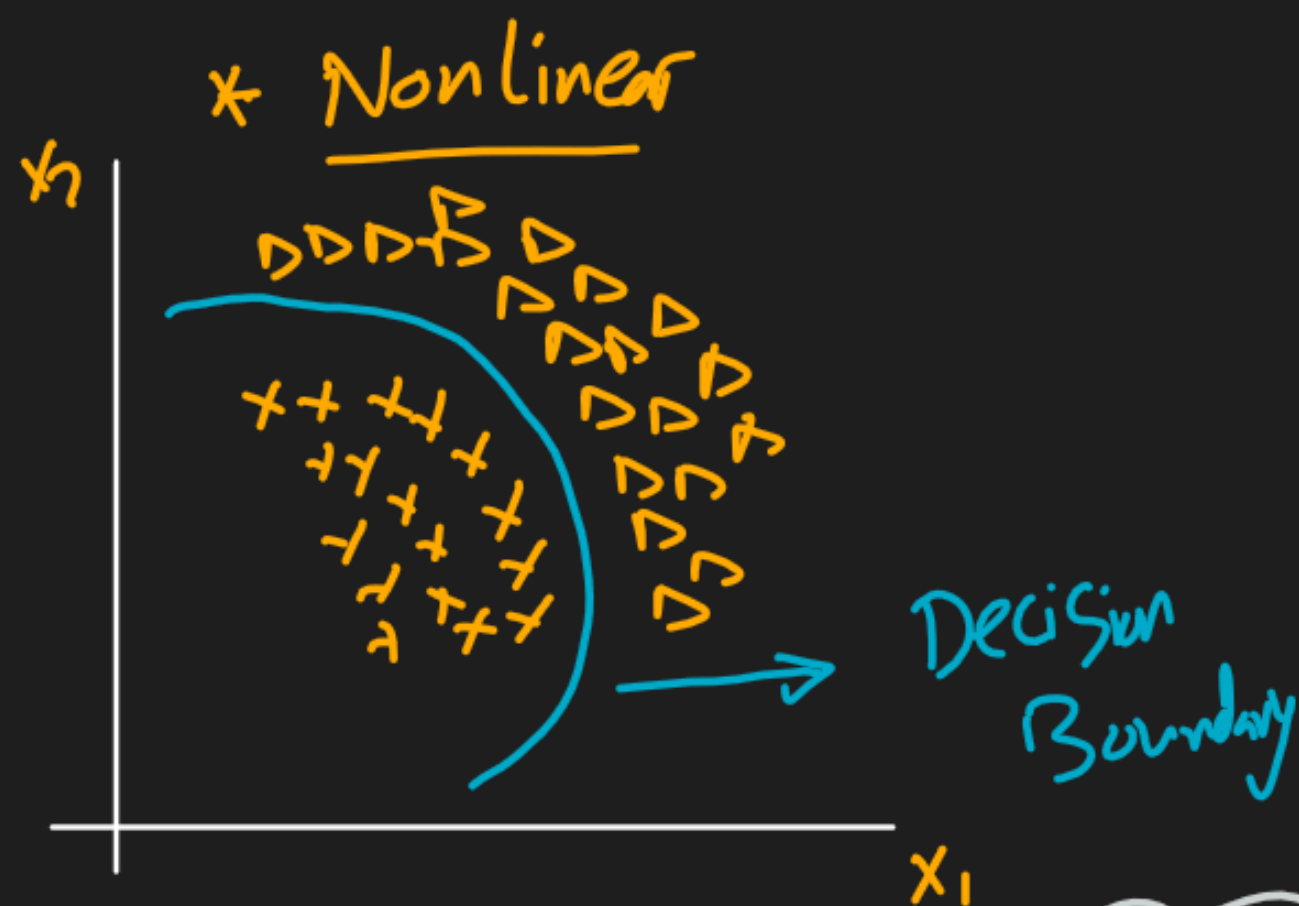
2- calculate gradients  $\frac{\partial J}{\partial w}$

3- update weights  $w^{\text{new}} = w^{\text{old}} - \eta \frac{\partial J}{\partial w}$

iter

till  
Converge

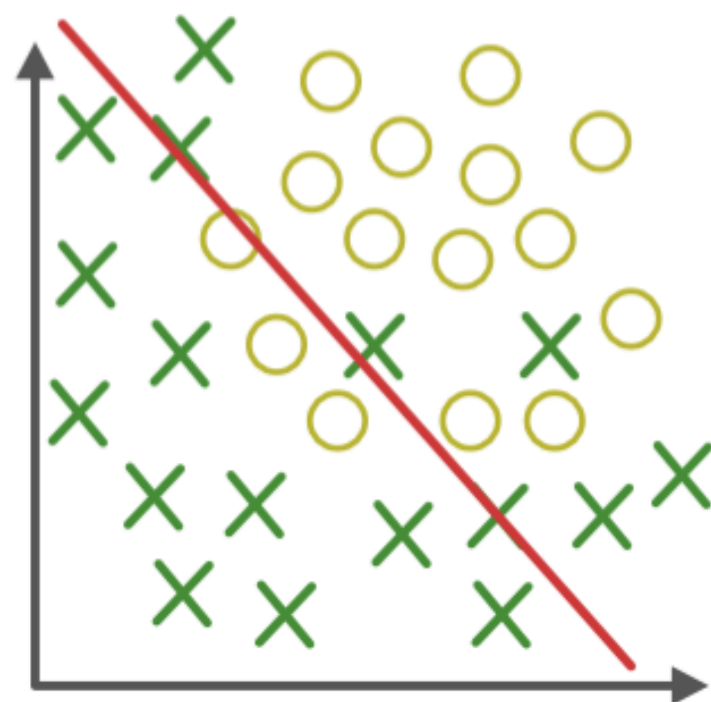
$w^{\text{new}} \approx w^{\text{old}}$  or Max. iters



$$y = \sigma(w_0 + w_1 x_1 + w_2 x_2 + \underbrace{w_3 x_1^2 + w_4 x_2^2 + w_5 x_1 x_2}_{\text{polynomial}})$$

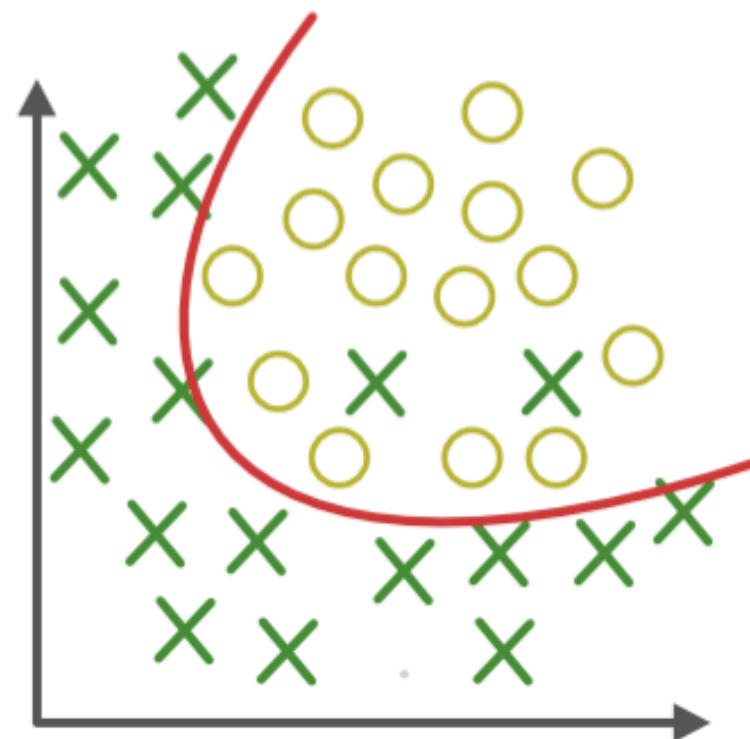
Polynomial  
features + Logistic  
Regression



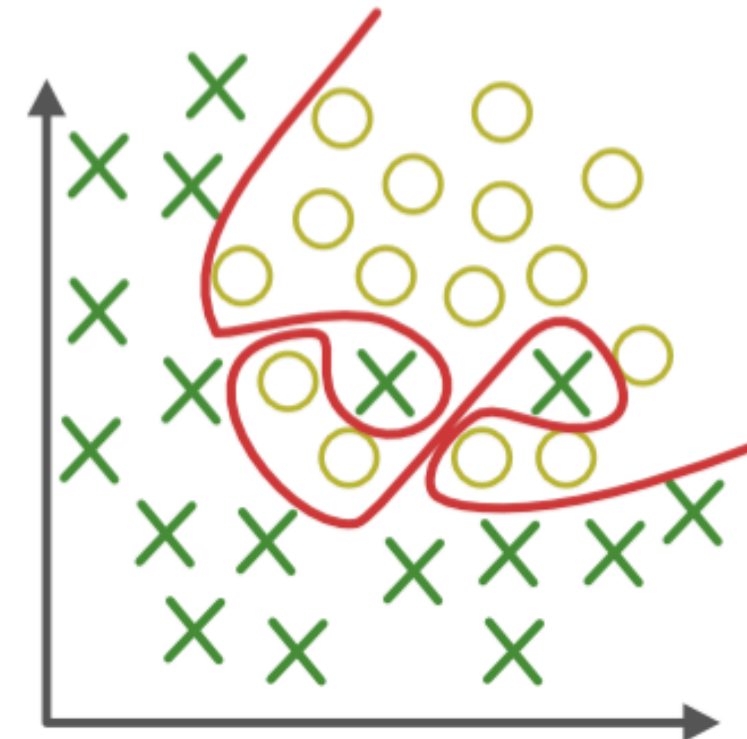


**Under-fitting**

(too simple to explain the variance)



**Appropriate-fitting**



**Over-fitting**

(forcefitting--too good to be true)



Train Error

Test Error



\* To reduce overfitting: Apply Penalty ( $L_1, L_2$ , Elastic)

→ Add Regularization term to Cost  $J_{\text{reg}}$

→ Apply optimization

Linear Regression

alpha  $\propto$  penalty

Control  
Regularization

Logistic Reg

$C \propto \frac{1}{\text{penalty}}$

check

penalty Compliant  
with Solver  
Solver Docs

# Stratify

