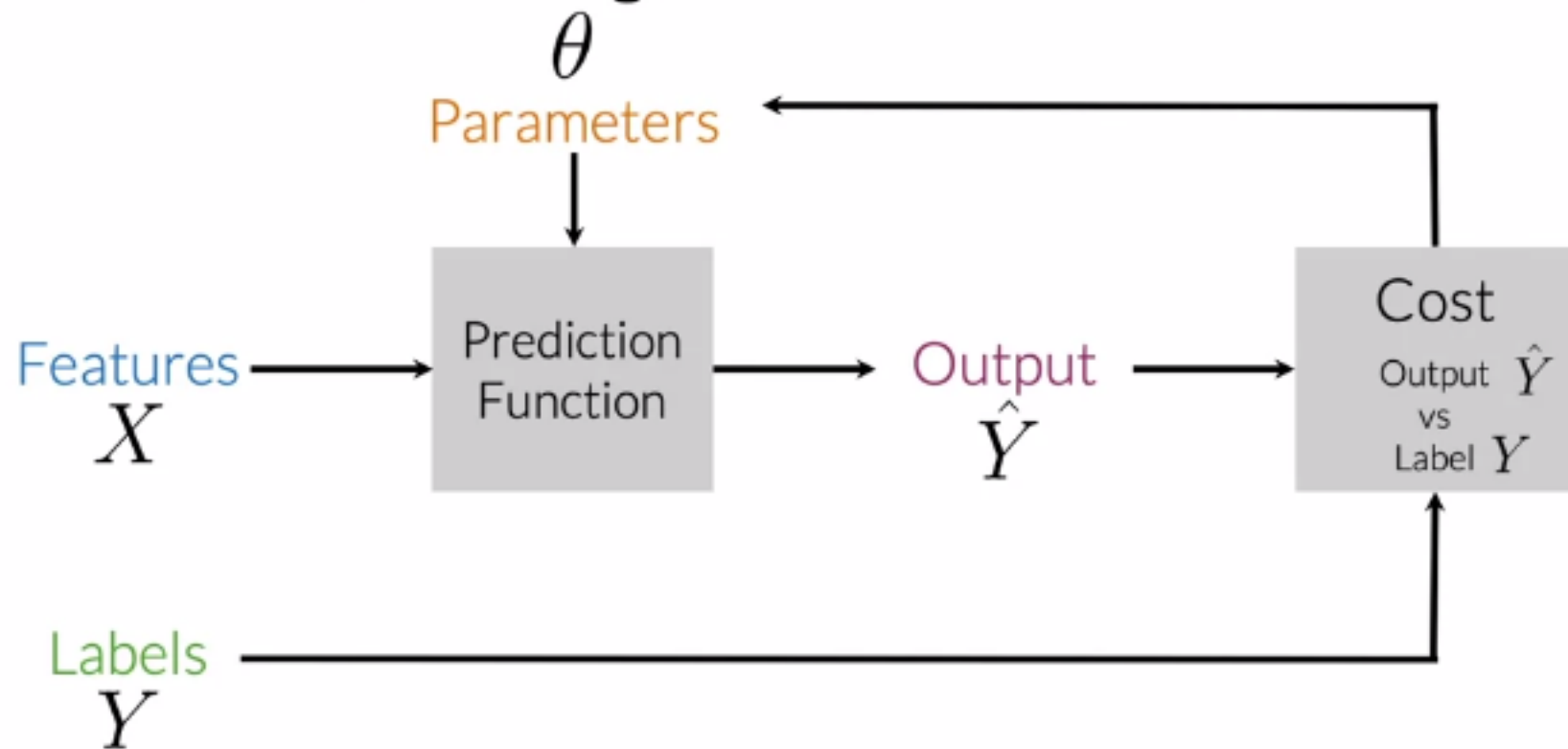


# Supervised ML (training)



# Sentiment analysis

Tweet: I am happy because I am learning NLP

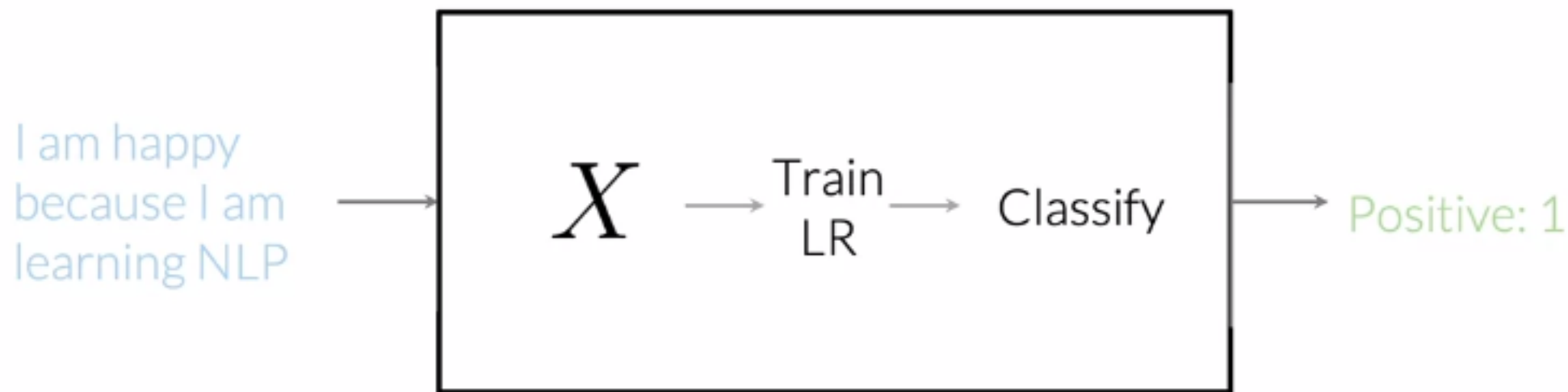
Positive: 1

Negative: 0

---

Logistic regression

# Sentiment analysis



# Vocabulary

Tweets:

[tweet\_1, tweet\_2, ..., tweet\_m]



I am happy because I am learning NLP

...

...

...

I hated the movie

$V =$

[I, am, happy, because, learning, NLP, ... hated, the, movie]

# Feature extraction

I am happy because I am learning NLP

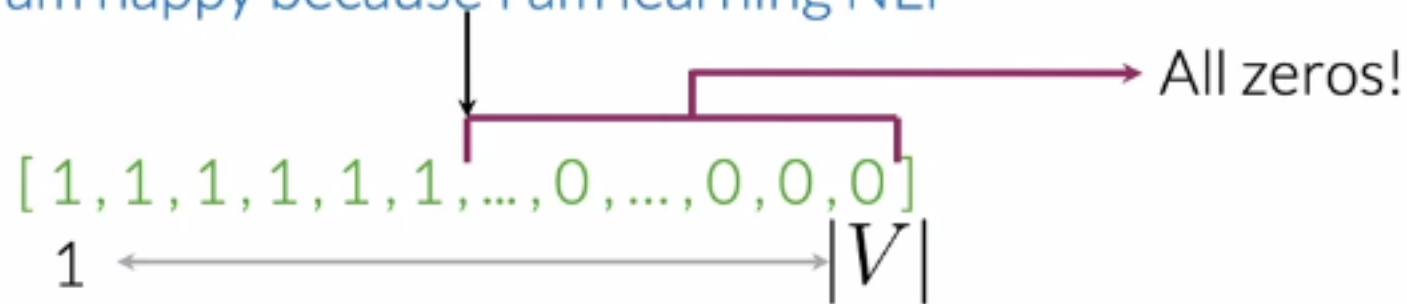
[ I , am, happy, because, learning, NLP, ... hated, the, movie ]

↓	↓	↓	↓	↓	↓	↓	↓	↓	↓
[ 1,	1,	1,	1,	1,	1,	...	0,	0,	0 ]

A lot of zeros! That's a sparse representation.

# Problems with sparse representations

I am happy because I am learning NLP



# Problems with sparse representations

I am happy because I am learning NLP

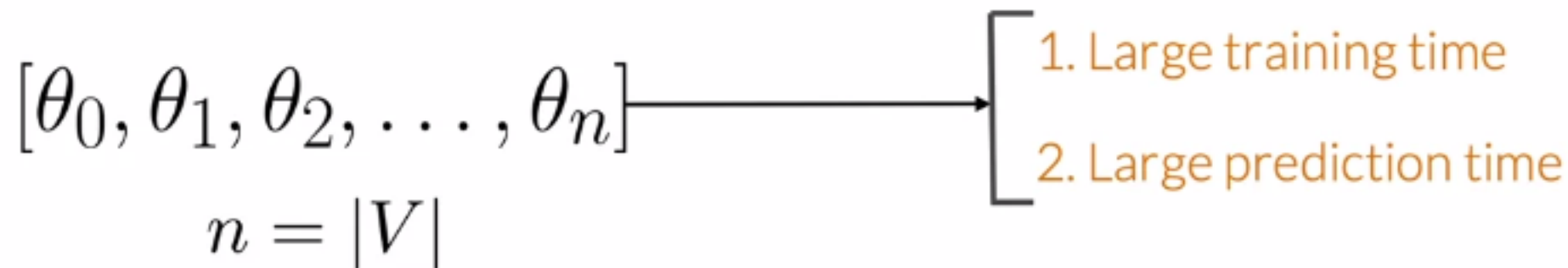


$$[\theta_0, \theta_1, \theta_2, \dots, \theta_n]$$

$$n = |V|$$

# Problems with sparse representations

I am happy because I am learning NLP





# Positive and negative counts

## Corpus

I am happy because I am learning NLP

I am happy

I am sad, I am not learning NLP

I am sad

# Positive and negative counts

## Corpus

I am happy because I am learning NLP

I am happy

I am sad, I am not learning NLP

I am sad

## Vocabulary

I

am

happy

because

learning

NLP

sad

not

# Positive and negative counts

## Positive tweets

I am happy because I am learning NLP

I am happy

## Negative tweets

I am sad, I am not learning NLP

I am sad

# Positive and negative counts

Positive tweets

I am happy because I am learning NLP

I am happy

---

Vocabulary

---

I

am

happy

because

learning

NLP

sad

not

---

# Positive and negative counts

Positive tweets

I am happy because I am learning NLP

I am happy

Vocabulary	PosFreq (1)
I	3
am	3
happy	2
because	1
learning	1
NLP	1
sad	0
not	0

## Positive and negative counts

Vocabulary	NegFreq (0)
I	3
am	3
happy	0
because	0
learning	1
NLP	1
sad	2
not	1

Negative tweets

I am sad, I am not learning NLP

I am sad

## Word frequency in classes

Vocabulary	PosFreq (1)	NegFreq (0)
I	3	3
am	3	3
happy	2	0
because	1	0
learning	1	1
NLP	1	1
sad	0	1
not	0	1

## Word frequency in classes

Vocabulary	PosFreq (1)	NegFreq (0)
I	3	3
am	3	3
happy	2	0
because	1	0
learning	1	1
NLP	1	1
sad	0	1
not	0	1

*freqs*: dictionary mapping from  
(word, class) to frequency



## Word frequency in classes

Vocabulary	PosFreq (1)	NegFreq (0)
I	3	3
am	3	3
happy	2	0
because	1	0
learning	1	1
NLP	1	1
sad	0	2
not	0	1

*freqs*: dictionary mapping from  
(word, class) to frequency

# Feature extraction

*freqs*: dictionary mapping from (word, class) to frequency

# Feature extraction

*freqs*: dictionary mapping from (word, class) to frequency

$$X_m = [ \quad \quad \quad ]$$



Features of  
tweet m

# Feature extraction

*freqs*: dictionary mapping from (word, class) to frequency

$$X_m = [1, \quad ]$$

  
Features of tweet m      Bias

# Feature extraction

*freqs*: dictionary mapping from (word, class) to frequency

$$X_m = [1, \sum_w \textit{freqs}(w, 1), \quad ]$$

Diagram illustrating the feature extraction formula:

- $X_m$  is the feature vector for tweet  $m$ .
- $1$  is the bias term.
- $\sum_w \textit{freqs}(w, 1)$  is the sum of positive frequencies for the tweet.

Labels below the formula:

- Features of tweet  $m$  (points to  $X_m$ )
- Bias (points to  $1$ )
- Sum Pos. Frequencies (points to  $\sum_w \textit{freqs}(w, 1)$ )

# Feature extraction

*freqs*: dictionary mapping from (word, class) to frequency

$$X_m = [1, \sum_w \textit{freqs}(w, 1), \sum_w \textit{freqs}(w, 0)]$$

Diagram illustrating the feature extraction formula for tweet  $m$ :

- $X_m$ : Features of tweet  $m$
- $1$ : Bias
- $\sum_w \textit{freqs}(w, 1)$ : Sum Pos. Frequencies
- $\sum_w \textit{freqs}(w, 0)$ : Sum Neg. Frequencies

# Feature extraction

I am sad, I am not learning NLP

# Feature extraction

Vocabulary	PosFreq (1)
I	3
am	3
happy	2
because	1
learning	1
NLP	1
sad	0
not	0

I am sad, I am not learning NLP



# Feature extraction

Vocabulary	PosFreq (1)
I	3
am	3
happy	2
because	1
learning	1
NLP	1
sad	0
not	0

I am sad, I am not learning NLP

$$X_m = [1, \sum_w \text{freqs}(w, 1), \sum_w \text{freqs}(w, 0)]$$

# Feature extraction

Vocabulary	PosFreq (1)
I	<u>3</u>
am	<u>3</u>
happy	2
because	1
learning	<u>1</u>
NLP	<u>1</u>
sad	<u>0</u>
not	<u>0</u>

I am sad, I am not learning NLP

$$X_m = [1, \sum_w \text{freqs}(w, 1), \sum_w \text{freqs}(w, 0)]$$

# Feature extraction

Vocabulary	PosFreq (1)
I	<u>3</u>
am	<u>3</u>
happy	2
because	1
learning	<u>1</u>
NLP	<u>1</u>
sad	<u>0</u>
not	<u>0</u>

I am sad, I am not learning NLP

$$X_m = [1, \sum_w \text{freqs}(w, 1), \sum_w \text{freqs}(w, 0)]$$



# Feature extraction

Vocabulary	NegFreq (0)
I	<u>3</u>
am	<u>3</u>
happy	0
because	0
learning	<u>1</u>
NLP	<u>1</u>
sad	<u>2</u>
not	<u>1</u>

I am sad, I am not learning NLP

$$X_m = [1, \sum_w \text{freqs}(w, 1), \sum_w \text{freqs}(w, 0)]$$

# Feature extraction

Vocabulary	NegFreq (0)
I	<u>3</u>
am	<u>3</u>
happy	0
because	0
learning	<u>1</u>
NLP	<u>1</u>
sad	<u>2</u>
not	<u>1</u>

I am sad, I am not learning NLP

$$X_m = [1, \sum_w \text{freqs}(w, 1), \sum_w \text{freqs}(w, 0)]$$

↓  
11

# Feature extraction

I am sad, I am not learning NLP

$$X_m = [1, \sum_w \textit{freqs}(w, 1), \sum_w \textit{freqs}(w, 0)]$$

# Feature extraction

I am sad, I am not learning NLP

$$X_m = [1, \sum_w \textit{freqs}(w, 1), \sum_w \textit{freqs}(w, 0)]$$



$$X_m = [1, 8, 11]$$

# Preprocessing: stop words and punctuation

@YMourri and @AndrewYNg are  
tuning a GREAT AI model at  
<https://deeplearning.ai!!!>



# Preprocessing: stop words and punctuation

@YMourri and @AndrewYNg are  
tuning a GREAT AI model at  
<https://deeplearning.ai!!!>

---

## Stop words

---

and  
is  
are  
at  
has  
for  
a

---

---

## Punctuation

---

,  
.  
:  
!  
"  
'

---

# Preprocessing: stop words and punctuation

@YMourri ~~and~~ @AndrewYNg ~~are~~  
tuning ~~a~~ GREAT AI model ~~at~~  
<https://deeplearning.ai!!!>

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## Stop words

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# Preprocessing: stop words and punctuation

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GREAT AI model  
<https://deeplearning.ai!!!>

@YMourri @AndrewYNg tuning  
GREAT AI model  
<https://deeplearning.ai>

---

## Stop words

---

and

is

a

at

has

for

of

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---

## Punctuation

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"

'

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# Preprocessing: Handles and URLs

@YMourri @AndrewYNg tuning GREAT AI model  
<https://deeplearning.ai>

# Preprocessing: Handles and URLs

~~@YMourri @AndrewYNg~~ tuning GREAT AI model  
~~<https://deeplearning.ai>~~



## Preprocessing: Handles and URLs

~~@YMourri @AndrewYNg~~ tuning GREAT AI model  
~~https://deeplearning.ai~~



tuning GREAT AI model

# Preprocessing: Stemming and lowercasing

tuning GREAT AI model

## Preprocessing: Stemming and lowercasing

tuning GREAT AI model

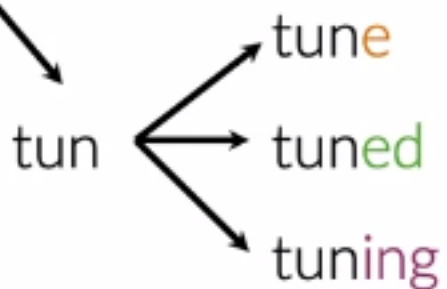


tun

The diagram illustrates the process of stemming. A black arrow points from the word 'tuning' in the phrase 'tuning GREAT AI model' (which is enclosed in a green rectangular box) down to the word 'tun'. This represents the reduction of the word to its root form.

## Preprocessing: Stemming and lowercasing

tuning GREAT AI model



## Preprocessing: Stemming and lowercasing

tuning GREAT AI model

tun

- tune
- tuned
- tuning

GREAT

Great

great

## Preprocessing: Stemming and lowercasing

tuning GREAT AI model

tun

- tune
- tuned
- tuning

GREAT  
Great  
great

→ great

## Preprocessing: Stemming and lowercasing

tuning GREAT AI model

tun

- tune
- tuned
- tuning

GREAT  
Great  
great

→ great

Preprocessed tweet:  
[tun, great, ai, model]

# General overview

I am Happy Because i am learning NLP @deeplearning



Preprocessing

[happy, learn, nlp]



# General overview

I am Happy Because i am learning NLP @deeplearning

↓ Preprocessing

[happy, learn, nlp]

↓ Feature Extraction

[1, 4, 2]

# General overview

I am Happy Because i am learning NLP @deeplearning

↓ Preprocessing

[happy, learn, nlp]

↓ Feature Extraction

Bias ← [1, 4, 2]

# General overview

I am Happy Because i am learning NLP @deeplearning

↓ Preprocessing

[happy, learn, nlp]

↓ Feature Extraction

Bias ← [1, 4, 2]

↓  
Sum positive frequencies

# General overview

I am Happy Because i am learning NLP @deeplearning

↓ Preprocessing

[happy, learn, nlp]

↓ Feature Extraction

Bias ← [1, 4, 2] → Sum negative frequencies

↓ Sum positive frequencies

# General overview

I am Happy Because i am  
learning NLP  
@deeplearning

I am sad not learning NLP

...

I am sad :(

# General overview

I am Happy Because i am  
learning NLP  
@deeplearning

[happy, learn, nlp]

[sad, not, learn, nlp]

I am sad not learning NLP →

...

...

[sad]

I am sad :(

# General overview

I am Happy Because i am  
learning NLP  
@deeplearning

I am sad not learning NLP

...

I am sad :(

[happy, learn, nlp]

[sad, not, learn, nlp]

...

[sad]

[[1, 40, 20],

[1, 20, 50],

...

[1, 5, 35]]

## General overview

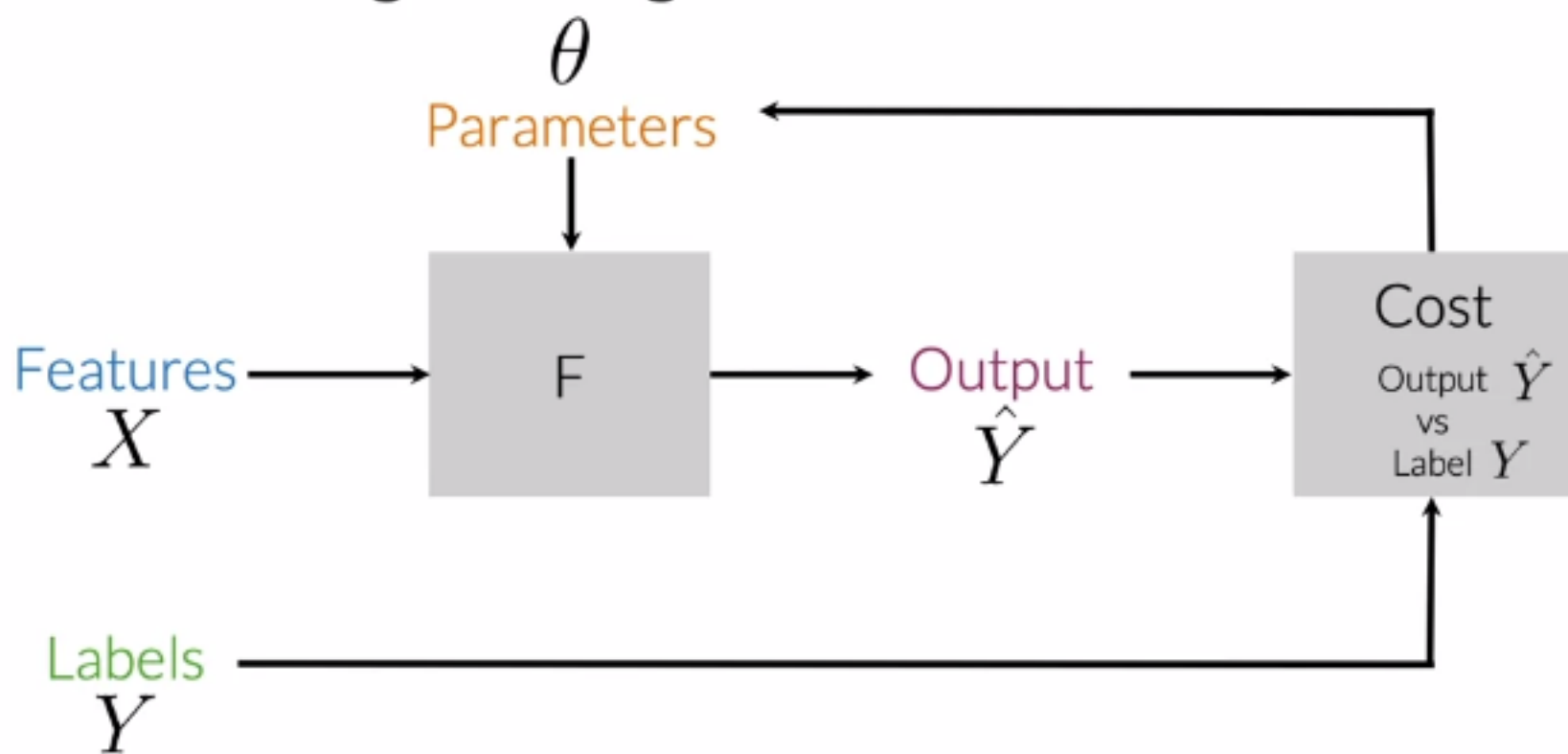
$$\begin{bmatrix} 1 & X_1^{(1)} & X_2^{(1)} \\ 1 & X_1^{(2)} & X_2^{(2)} \\ \vdots & \vdots & \vdots \\ 1 & X_1^{(m)} & X_2^{(m)} \end{bmatrix} \longleftrightarrow \begin{matrix} [[1, 40, 20], \\ [1, 20, 50], \\ \dots \\ [1, 5, 35]] \end{matrix}$$



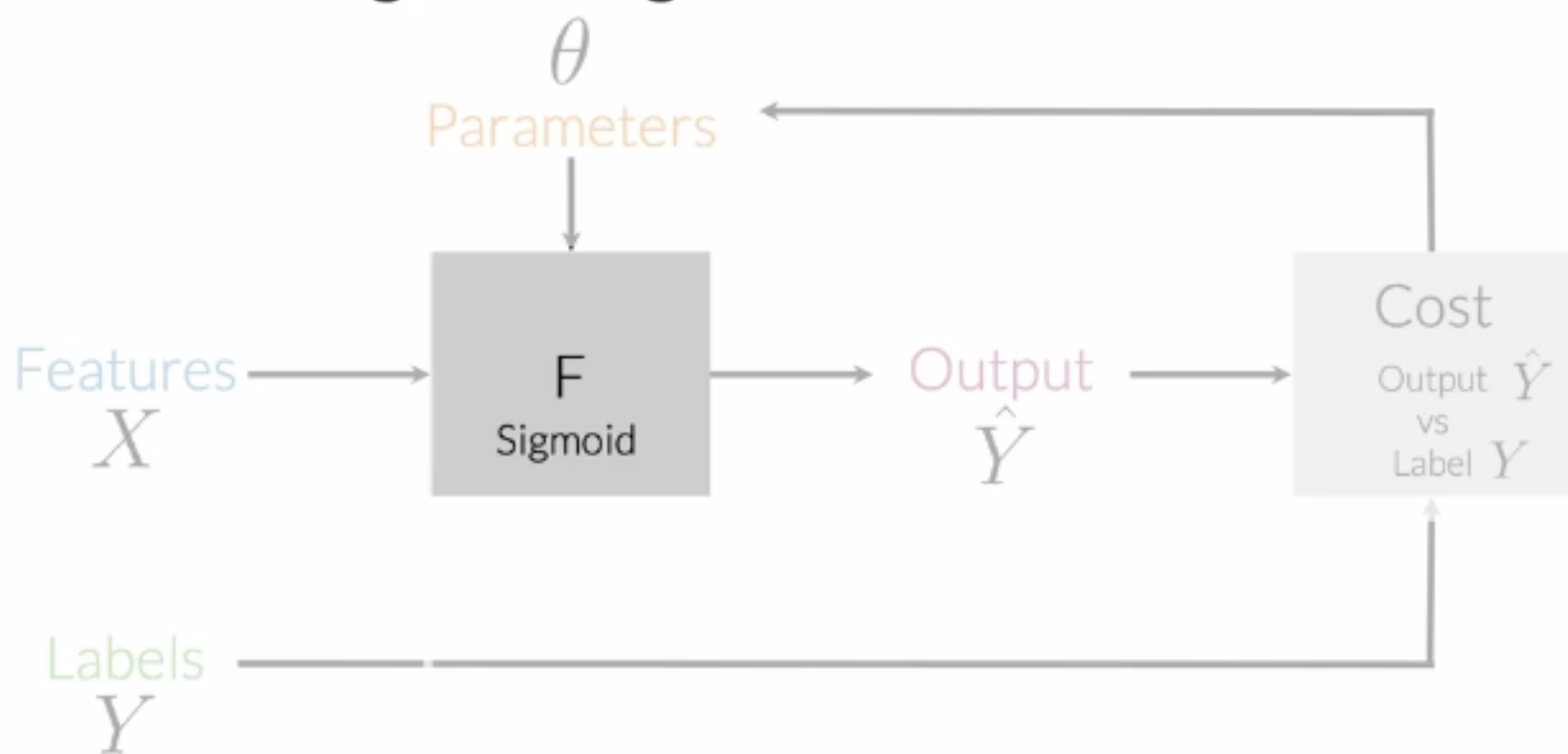
# General Implementation

```
freqs = build_freqs(tweets, labels) #Build frequencies dictionary
X = np.zeros((m, 3)) #Initialize matrix X
for i in range(m): #For every tweet
    p_tweet = process_tweet(tweets[i]) #Process tweet
    X[i, :] = extract_features(p_tweet, freqs) #Extract Features
```

# Overview of logistic regression



# Overview of logistic regression

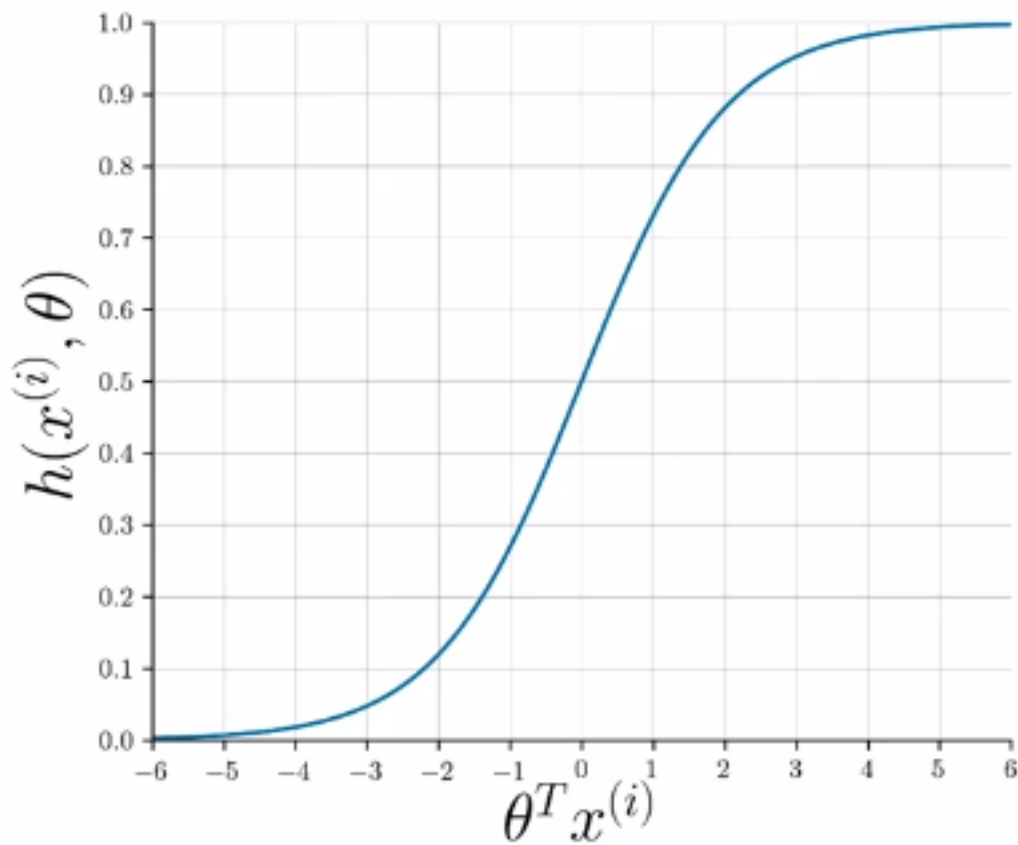


## Overview of logistic regression

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

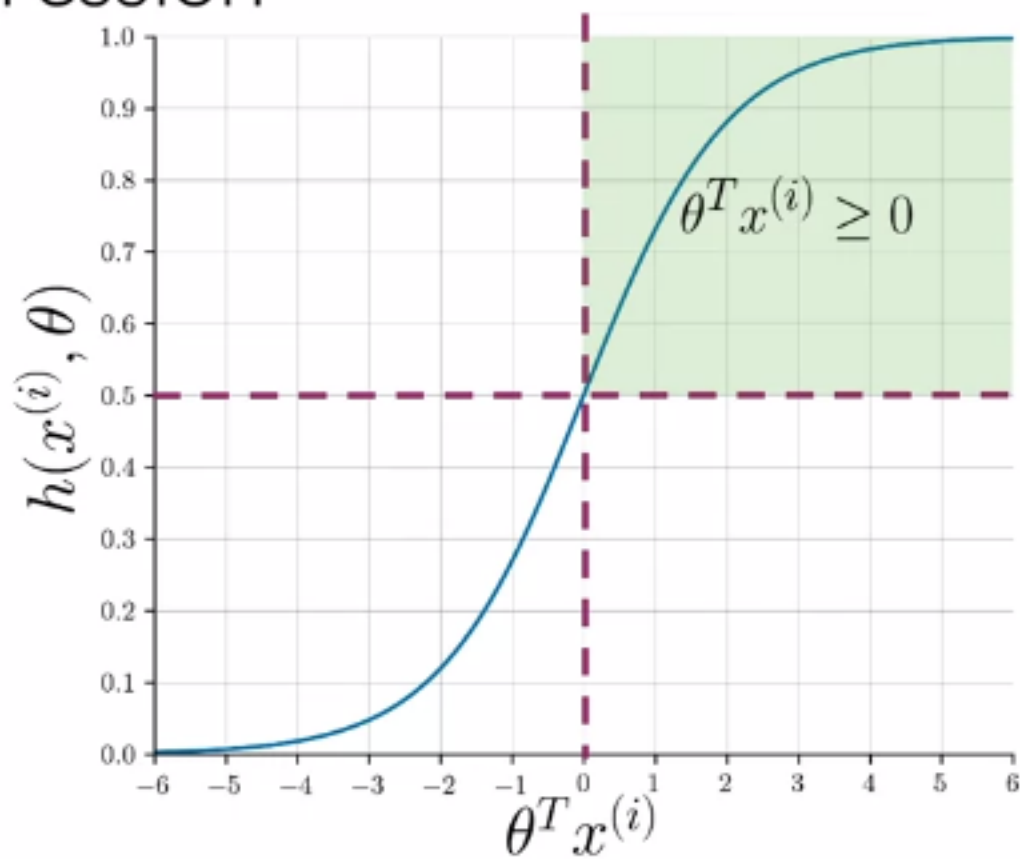
# Overview of logistic regression

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



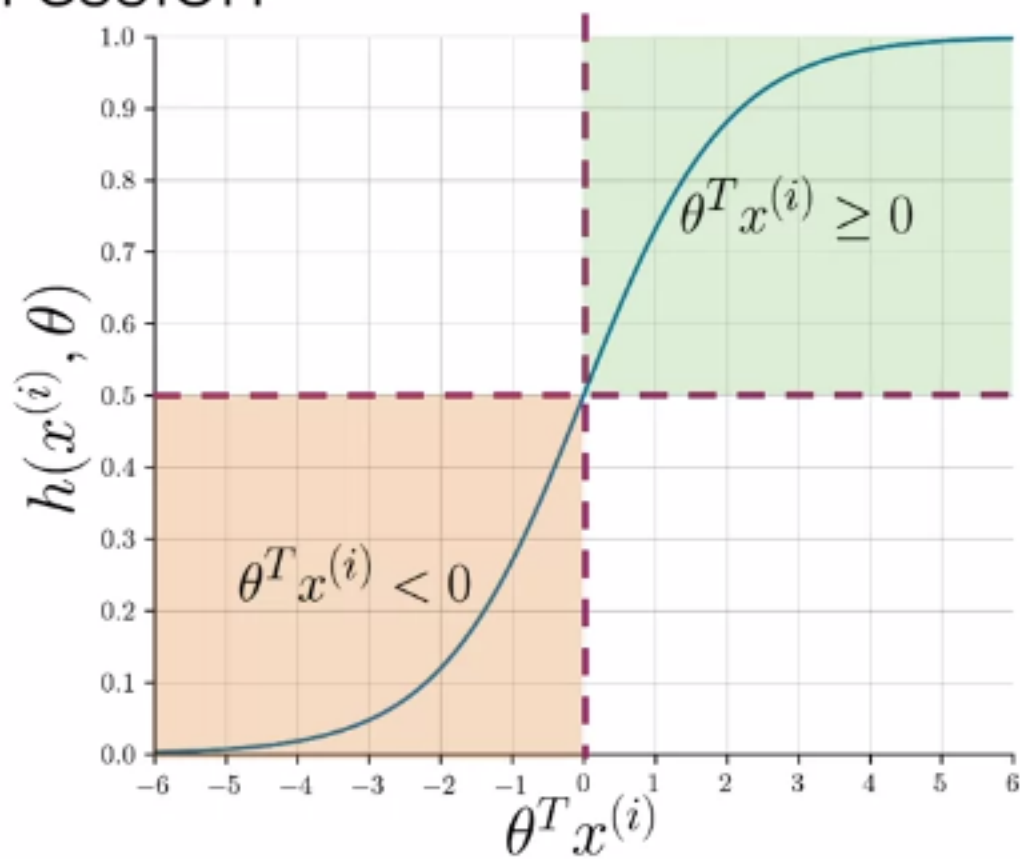
# Overview of logistic regression

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



# Overview of logistic regression

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



# Overview of logistic regression

@YMourri and  
@AndrewYNg are tuning a  
GREAT AI model



# Overview of logistic regression

@YMourri and  
@AndrewYNg are tuning a  
GREAT AI model



[tun, ai, great, model]

# Overview of logistic regression

@YMurri and  
@AndrewYNg are tuning a  
GREAT AI model

↓  
[tun, ai, great, model]

↓  
$$x^{(i)} = \begin{bmatrix} 1 \\ 3476 \\ 245 \end{bmatrix}$$

# Overview of logistic regression

@YMurri and  
@AndrewYNg are tuning a  
GREAT AI model

↓  
[tun, ai, great, model]

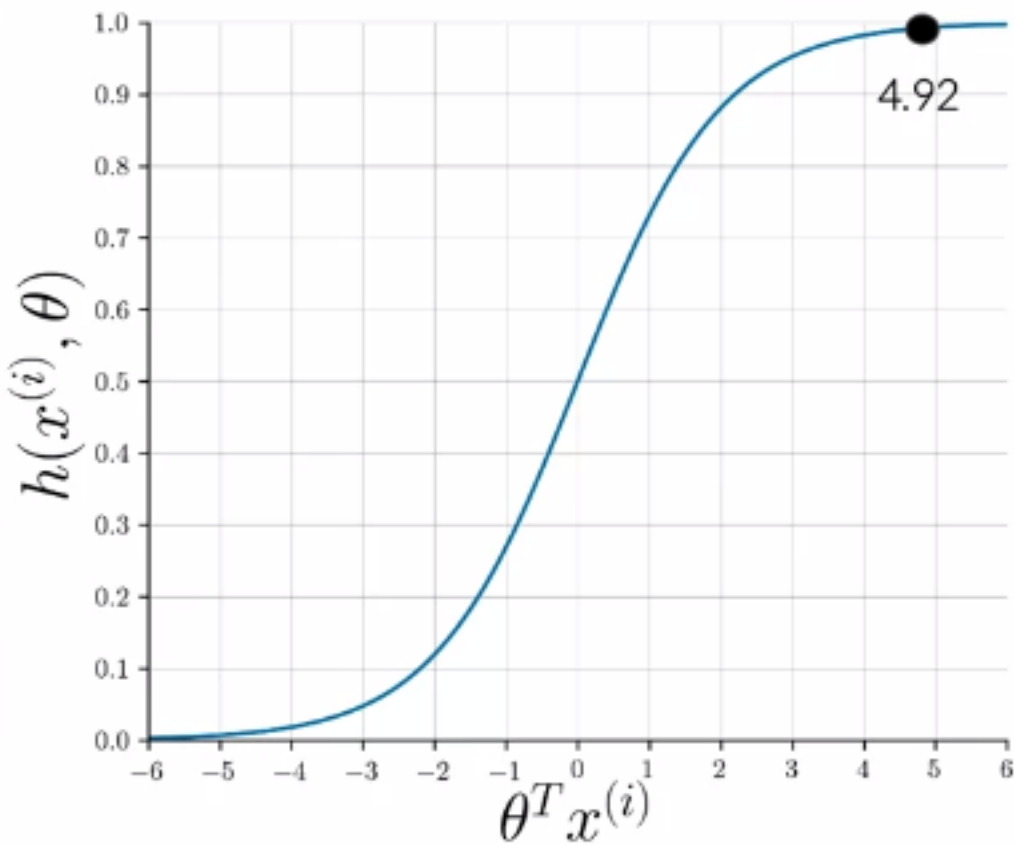
↓  
$$x^{(i)} = \begin{bmatrix} 1 \\ 3476 \\ 245 \end{bmatrix} \quad \theta = \begin{bmatrix} 0.00003 \\ 0.00150 \\ -0.00120 \end{bmatrix}$$

# Overview of logistic regression

@YMurri and  
@AndrewYNg are tuning a  
GREAT AI model

[tun, ai, great, model]

$$x^{(i)} = \begin{bmatrix} 1 \\ 3476 \\ 245 \end{bmatrix} \quad \theta = \begin{bmatrix} 0.00003 \\ 0.00150 \\ -0.00120 \end{bmatrix}$$

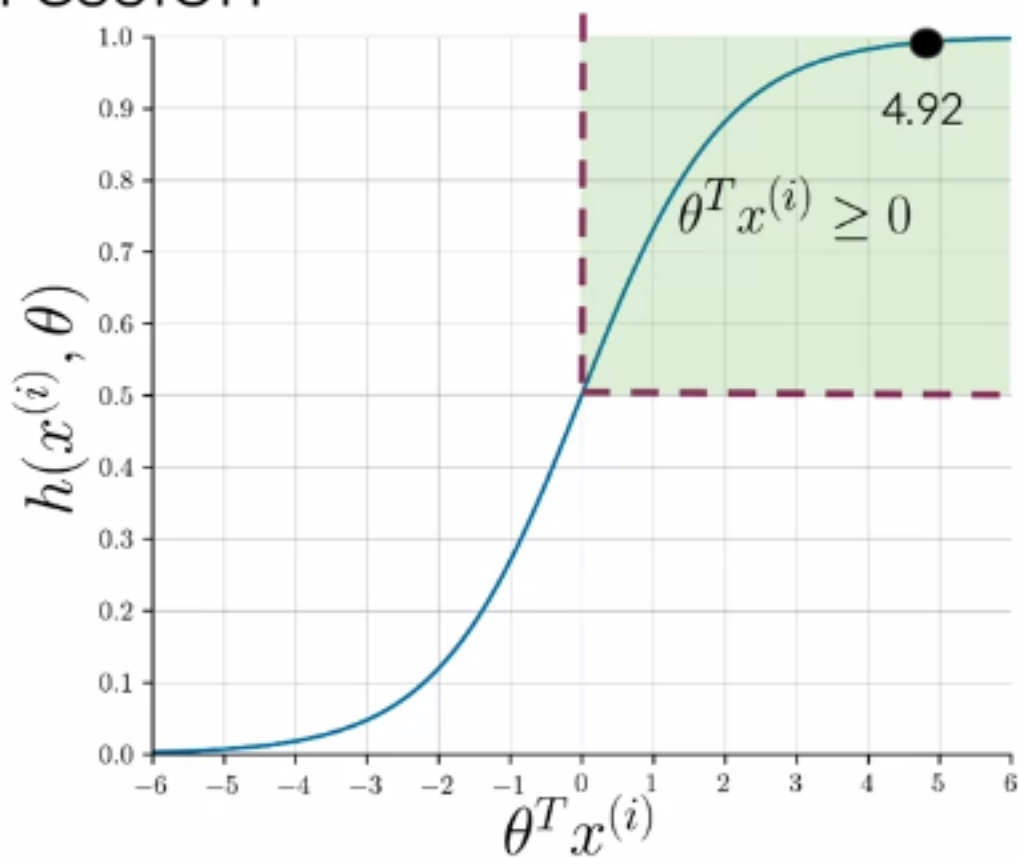


# Overview of logistic regression

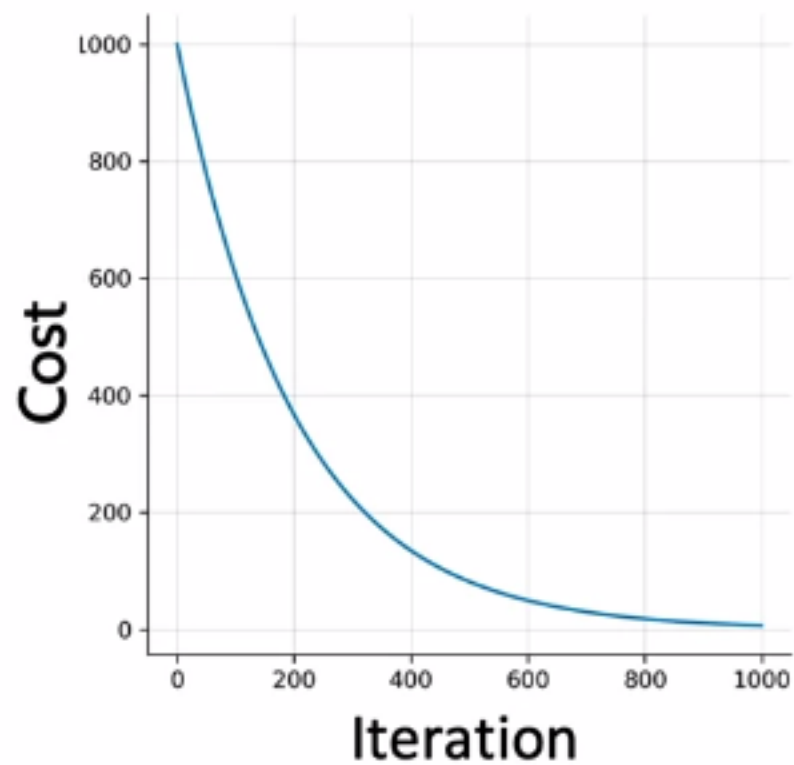
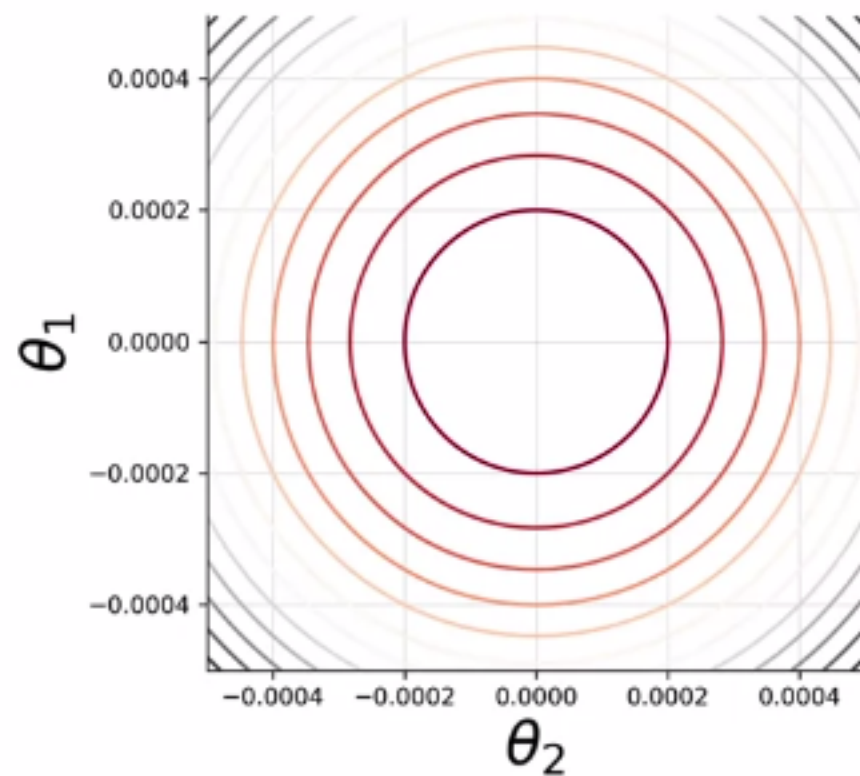
@YMurri and  
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[tun, ai, great, model]

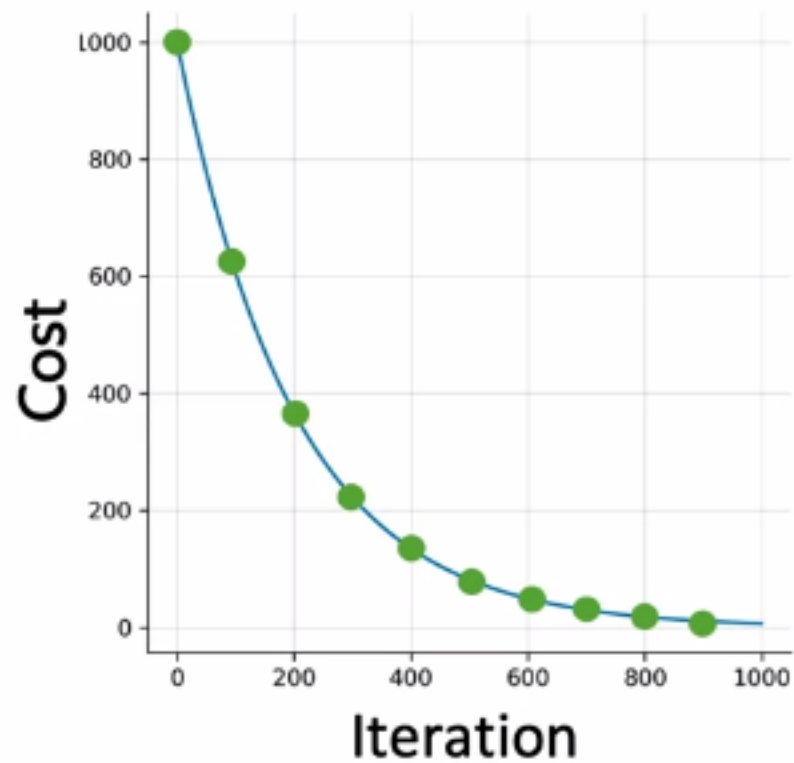
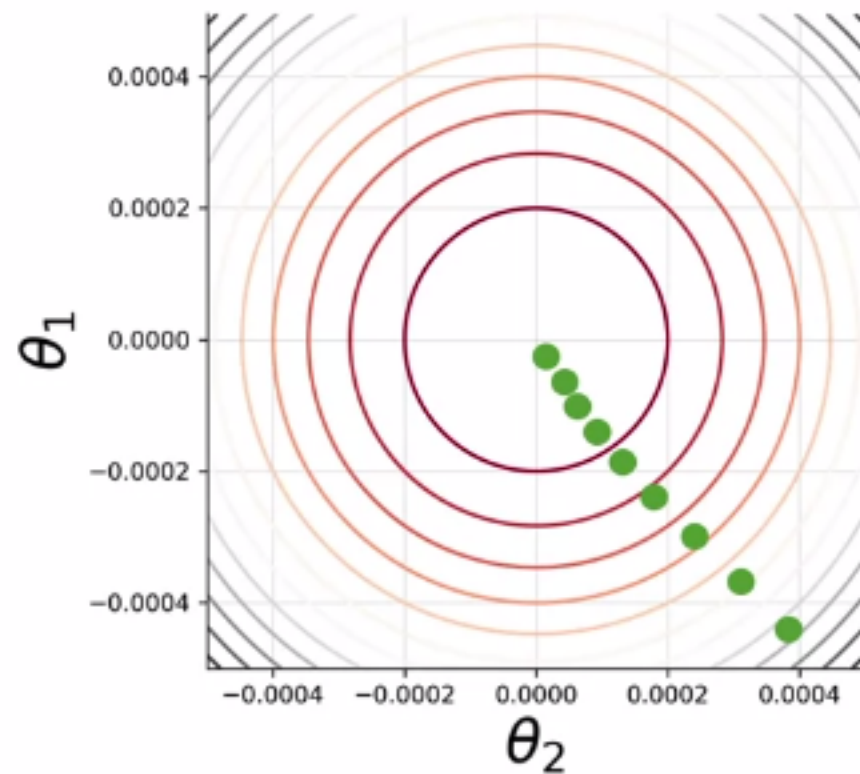
$$x^{(i)} = \begin{bmatrix} 1 \\ 3476 \\ 245 \end{bmatrix} \quad \theta = \begin{bmatrix} 0.00003 \\ 0.00150 \\ -0.00120 \end{bmatrix}$$



# Training LR



# Training LR



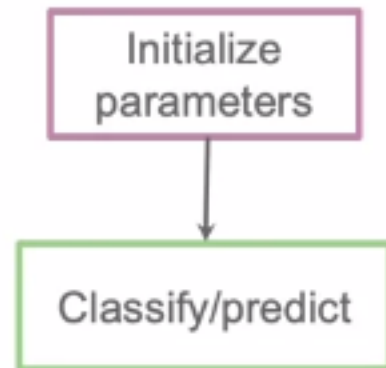
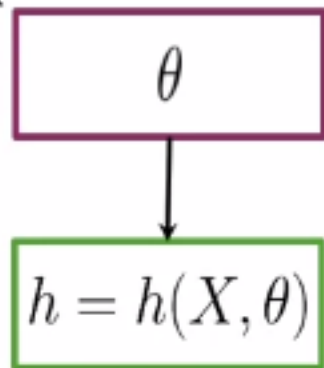
# Training LR

 $\theta$ 

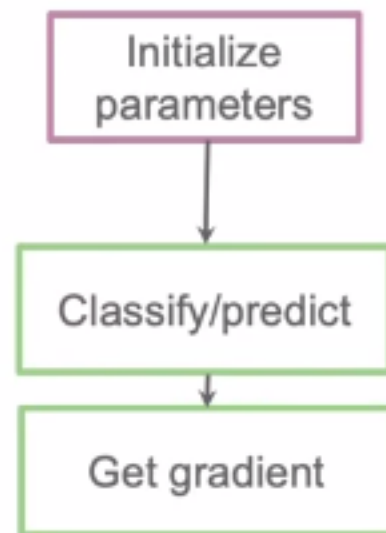
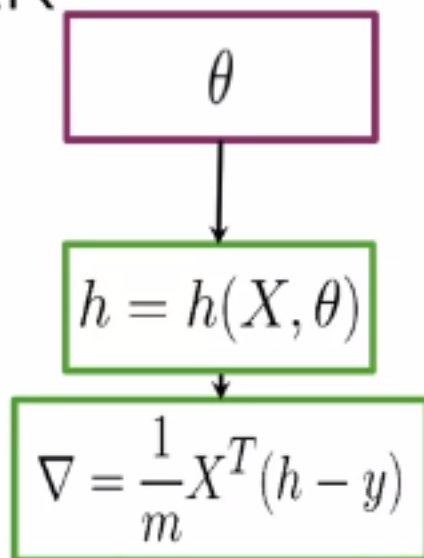
Initialize  
parameters



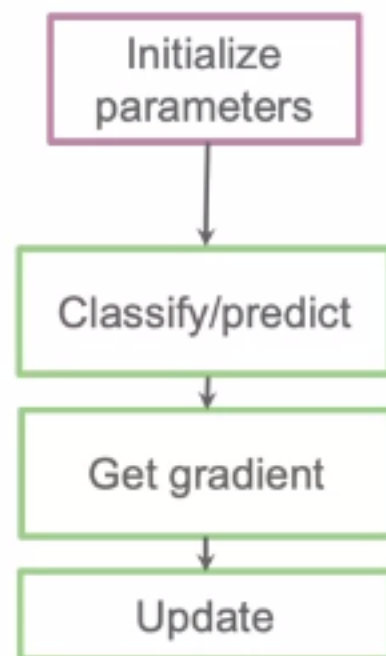
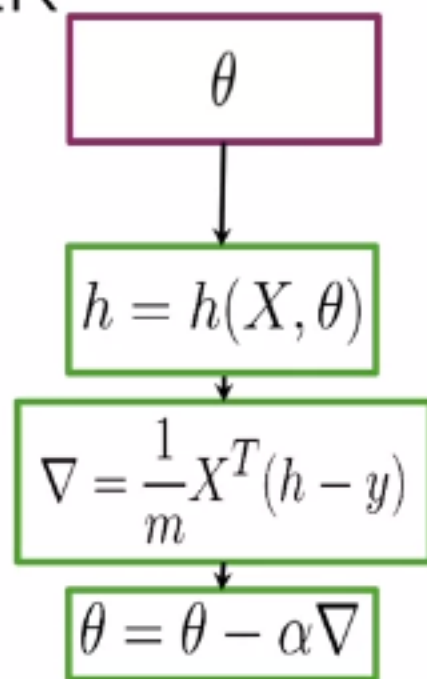
## Training LR



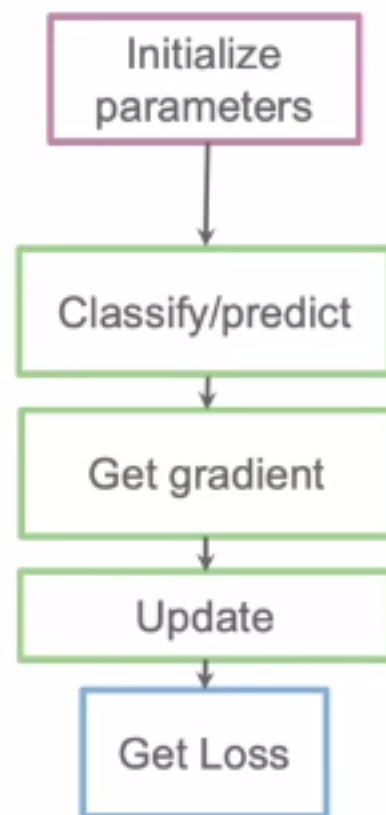
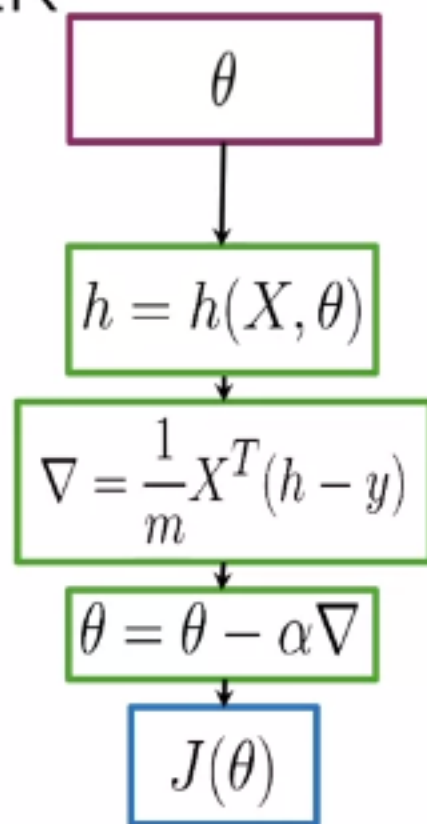
## Training LR



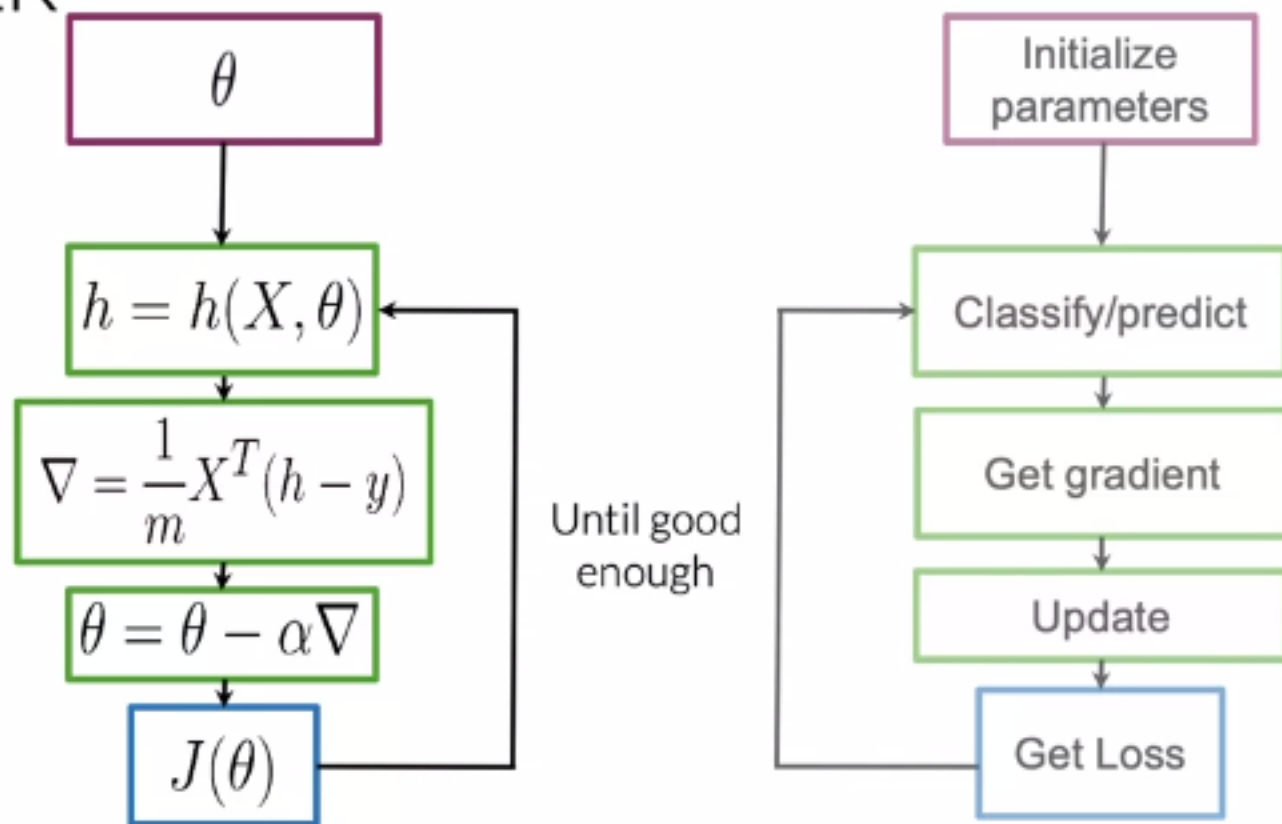
## Training LR



## Training LR



# Training LR



## Testing logistic regression

- $X_{val}$   $Y_{val}$   $\theta$

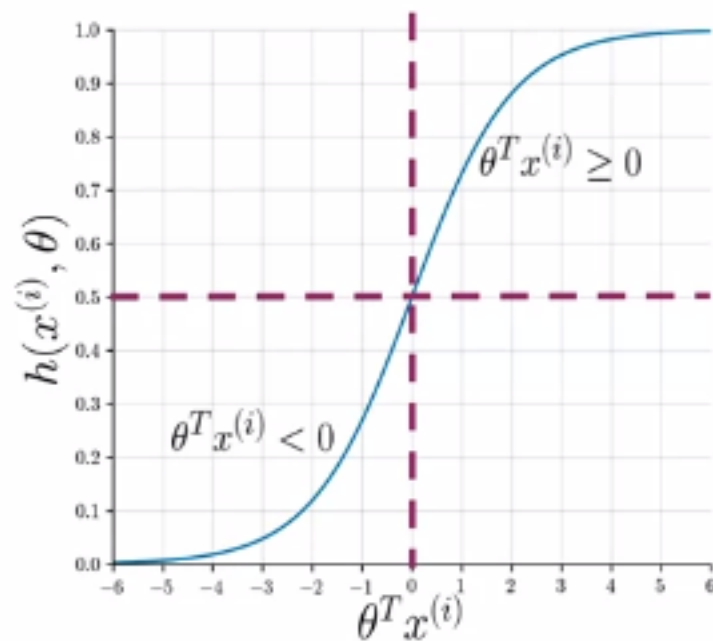
## Testing logistic regression

- $X_{val}$   $Y_{val}$   $\theta$   
 $h(X_{val}, \theta)$

# Testing logistic regression

- $X_{val}$   $Y_{val}$   $\theta$   
 $h(X_{val}, \theta)$

$$pred = h(X_{val}, \theta) \geq 0.5$$





## Testing logistic regression

- $X_{val}$   $Y_{val}$   $\theta$

$$h(X_{val}, \theta)$$

$$pred = h(X_{val}, \theta) \geq 0.5$$

$$\begin{bmatrix} 0.3 \\ 0.8 \\ 0.5 \\ \vdots \\ h_m \end{bmatrix}$$

## Testing logistic regression

- $X_{val}$   $Y_{val}$   $\theta$

$$h(X_{val}, \theta)$$

$$pred = h(X_{val}, \theta) \geq 0.5$$

$$\begin{bmatrix} 0.3 \\ 0.8 \\ 0.5 \\ \vdots \\ h_m \end{bmatrix} \geq 0.5$$

## Testing logistic regression

- $X_{val}$   $Y_{val}$   $\theta$

$$h(X_{val}, \theta)$$

$$pred = h(X_{val}, \theta) \geq 0.5$$

$$\begin{bmatrix} 0.3 \\ 0.8 \\ 0.5 \\ \vdots \\ h_m \end{bmatrix} \geq 0.5 = \begin{bmatrix} 0.3 \geq 0.5 \\ 0.8 \geq 0.5 \\ 0.5 \geq 0.5 \\ \vdots \\ pred_m \geq 0.5 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 1 \\ \vdots \\ pred_m \end{bmatrix}$$

## Testing logistic regression

- $X_{val} \ Y_{val} \ \theta$

$$h(X_{val}, \theta)$$

$$pred = h(X_{val}, \theta) \geq 0.5$$

$$\sum_{i=1}^m \frac{(pred^{(i)} == y_{val}^{(i)})}{m}$$

# Testing logistic regression

- $X_{val} \quad Y_{val} \quad \theta$   
 $h(X_{val}, \theta)$

$$pred = h(X_{val}, \theta) \geq 0.5$$

$$\sum_{i=1}^m \frac{(pred^{(i)} == y_{val}^{(i)})}{m}$$

$$\begin{bmatrix} 0 \\ 1 \\ 1 \\ \vdots \\ pred_m \end{bmatrix} == \begin{bmatrix} 0 \\ 0 \\ 1 \\ \vdots \\ Y_{val_m} \end{bmatrix}$$
$$\begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \\ pred_m == Y_{val_m} \end{bmatrix}$$

## Testing logistic regression

- $X_{val} \ Y_{val} \ \theta$

$$h(X_{val}, \theta)$$

$$pred = h(X_{val}, \theta) \geq 0.5$$

$$\sum_{i=1}^m \frac{(pred^{(i)} == y_{val}^{(i)})}{m}$$

## Testing logistic regression

$$Y_{val} = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \\ 1 \end{bmatrix} \quad pred = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

## Testing logistic regression

$$Y_{val} = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \\ 1 \end{bmatrix} \quad pred = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 1 \end{bmatrix} \quad (Y_{val} == pred) = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 1 \\ 1 \end{bmatrix}$$



## Testing logistic regression

$$Y_{val} = \begin{bmatrix} 0 \\ 1 \\ \underline{1} \\ 0 \\ 1 \end{bmatrix} \quad pred = \begin{bmatrix} 0 \\ 1 \\ \underline{0} \\ 0 \\ 1 \end{bmatrix} \quad (Y_{val} == pred) = \begin{bmatrix} 1 \\ 1 \\ \underline{0} \\ 1 \\ 1 \end{bmatrix}$$
$$\text{accuracy} = \frac{4}{5} = 0.8$$

## Cost function for logistic regression

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

## Cost function for logistic regression

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

## Cost function for logistic regression

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

## Cost function for logistic regression

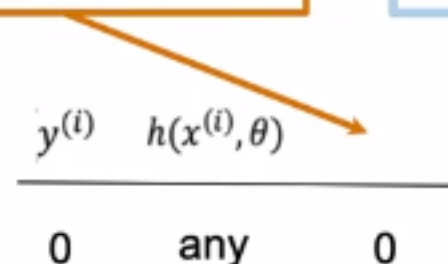
$$J(\theta) = -\frac{1}{m} \sum_{i=1}^m [y^{(i)} \log h(x^{(i)}, \theta) + (1 - y^{(i)}) \log(1 - h(x^{(i)}, \theta))]$$

## Cost function for logistic regression

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

$y^{(i)}$	$h(x^{(i)}, \theta)$
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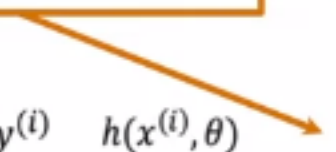
## Cost function for logistic regression

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


$y^{(i)}$	$h(x^{(i)}, \theta)$
0	0
any	0

## Cost function for logistic regression

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

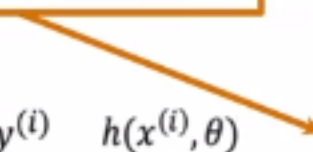


$y^{(i)}$	$h(x^{(i)}, \theta)$	
0	any	0
1	0.99	$\sim 0$



## Cost function for logistic regression

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




$y^{(i)}$	$h(x^{(i)}, \theta)$	
0	any	0
1	0.99	$\sim 0$
1	$\sim 0$	-inf

## Cost function for logistic regression


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

$y^{(i)} \quad h(x^{(i)}, \theta)$



## Cost function for logistic regression


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



$y^{(i)}$	$h(x^{(i)}, \theta)$
1	any
	0

## Cost function for logistic regression


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



$y^{(i)}$	$h(x^{(i)}, \theta)$	
1	any	0
0	0.01	$\sim 0$

## Cost function for logistic regression

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



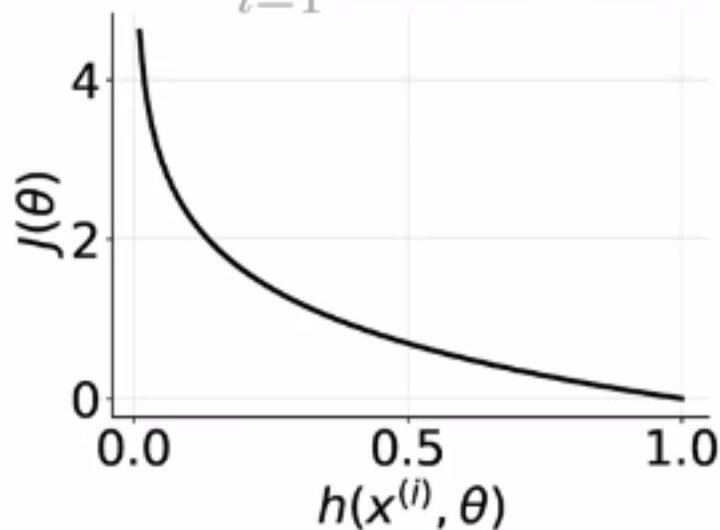
$y^{(i)}$	$h(x^{(i)}, \theta)$	
1	any	0
0	0.01	$\sim 0$
0	$\sim 1$	$-\text{Inf}$

## Cost function for logistic regression

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

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## Cost function for logistic regression

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