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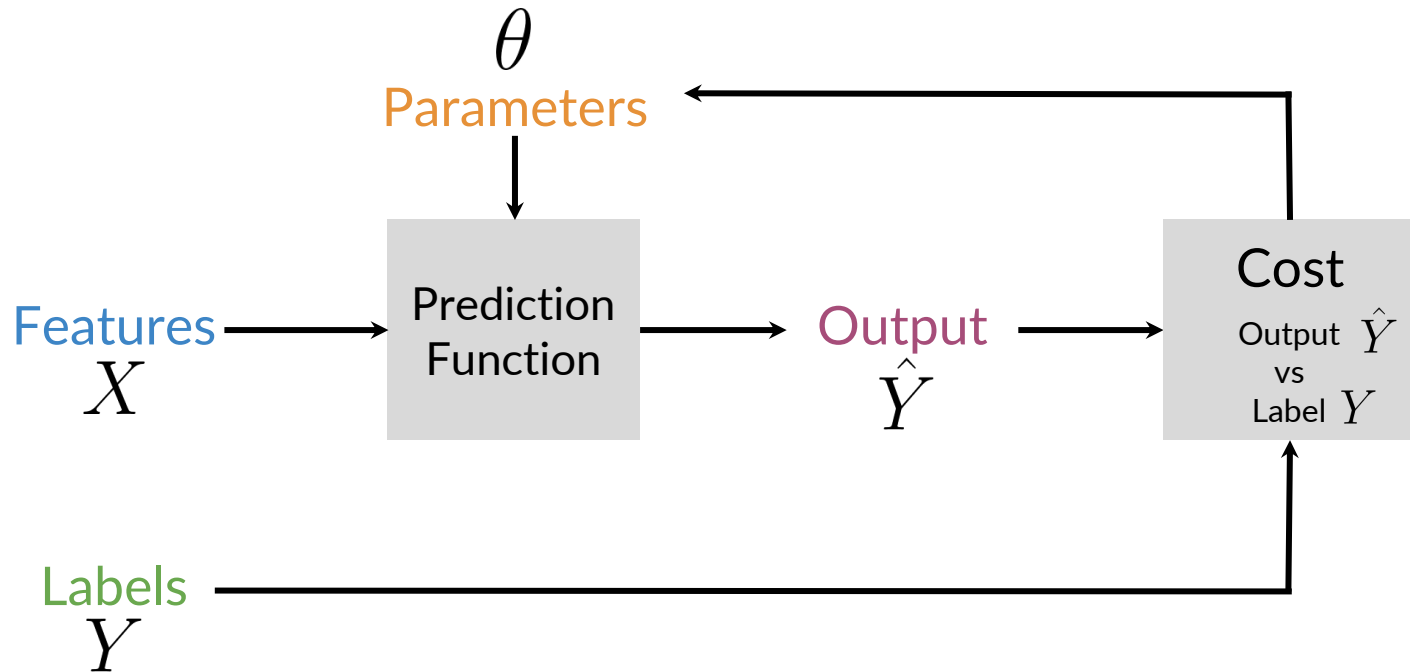
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Supervised ML and Sentiment Analysis

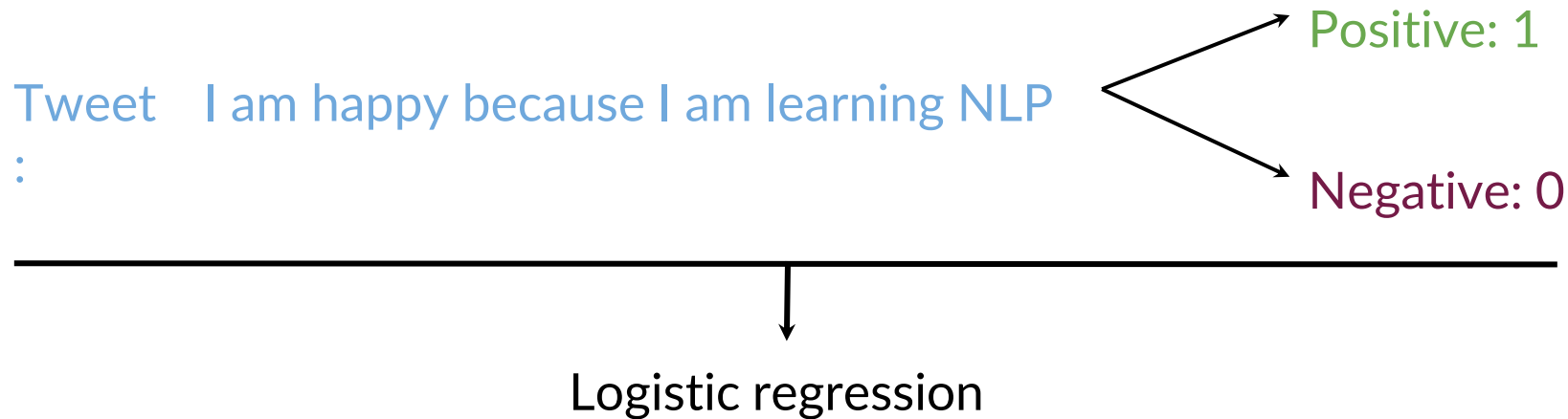
Outline

- Review Supervised ML
- Build your own tweet classifier!

Supervised ML (training)

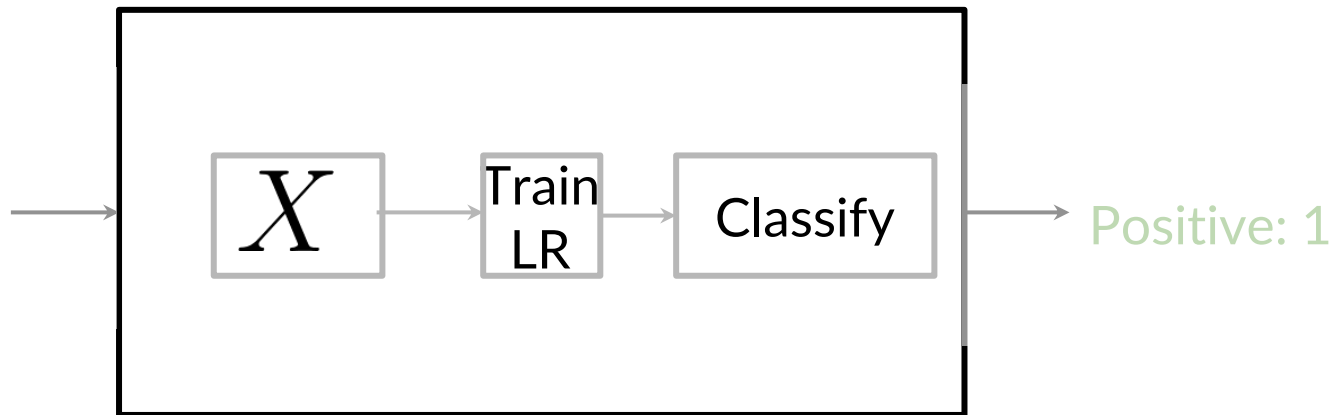


Sentiment analysis



Sentiment analysis

I am happy
because I am
learning NLP



Summary

- Features, Labels \longrightarrow Train \longrightarrow Predict
- Extract features \longrightarrow Train-LR \longrightarrow Predict sentiment



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Vocabulary and Feature Extraction

Outline

- Vocabulary
- Feature extraction
- Sparse representations and some of their issues

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

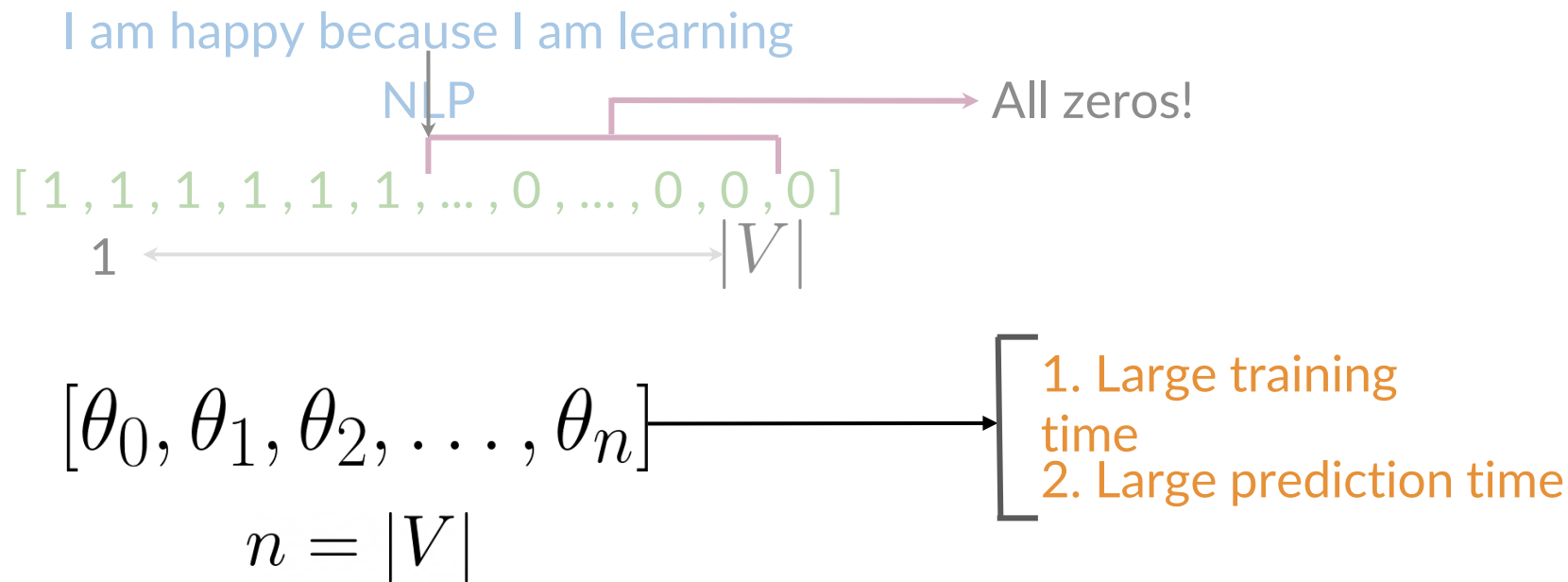
I am happy because I am learning NLP

[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



Summary

- Vocabulary: set of unique words
- Vocabulary, Text \longrightarrow [1 0 1 .. 0 .. 1 .. 0]
- Sparse representations are problematic for training and prediction times



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Negative and Positive Frequencies

Outline

- Populate your vocabulary with a frequency count for each class

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	PosFreq (1)
------------	-------------

I

am

happy

because

learning

NLP

sad

not

0

Positive and negative counts

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

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

Summary

- Divide tweet corpus into two classes: positive and negative
 - Count each time each word appears in either class
- Feature extraction for training and prediction!



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Feature extraction with frequencies

Outline

- Extract features from your frequencies dictionary to create a features vector

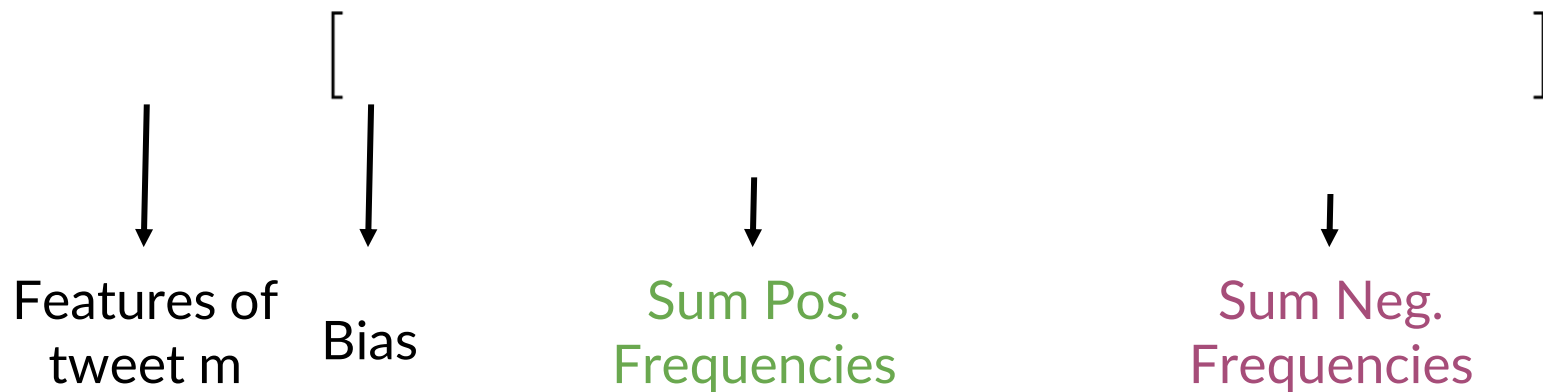
Word frequency in classes

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

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

I am sad, I am not learning NLP

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

↓

8

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

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



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

Summary

- Dictionary mapping (word,class) to frequencies

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

→ Cleaning unimportant information from your tweets



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Preprocessing

Outline

- Removing stopwords, punctuation, handles and URLs
- Stemming
- Lowercasing

Preprocessing: stop words and punctuation

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

Stop words	Punctuation
and	,
is	.
are	:
at	!
has	"
for	'
a	

Preprocessing: stop words and punctuation

@YMourri and @AndrewYNg are
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<https://deeplearning.ai!!!>

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

Stop words

and

is

are

at

has

for

a

Punctuation

,

.

:

!

“

‘

Preprocessing: stop words and punctuation

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

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

Stop words

and
is
a
at
has
for
of

Punctuation

,
.
:
!
"
,

Preprocessing: Handles and URLs

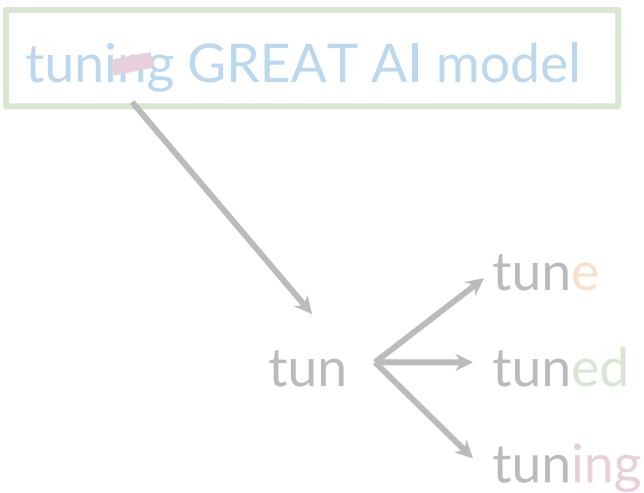
~~@YMurri @AndrewYNg tuning GREAT AI
model~~

<https://deeplearning.ai>



tuning GREAT AI model

Preprocessing: Stemming and lowercasing



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

Summary

- Stop words, punctuation, handles and URLs
- Stemming
- Lowercasing
- Less unnecessary info → Better times



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Putting it all together

Outline

- Generalize the process
- How to code it!

General overview

I am Happy Because i am learning NLP @deeplearning

↓ Preprocessing

[happy, learn, nlp]

↓ Feature Extraction

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

↓
Sum positive frequencies

General overview

$$\begin{bmatrix} 1 & X_1^{(1)} & X_2^{(1)} \\ 1 & X_1^{(2)} & X_2^{(2)} \\ \vdots & \vdots & \vdots \\ 1 & X_1^{(m)} & X_2^{(m)} \end{bmatrix}$$



$[1, 40, 20],$
 $[1, 20, 50],$
...
 $[1, 5,$
 $35]]$

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
```

Summary

- Implement the feature extraction algorithm for your entire set of tweets
- Almost ready to train!



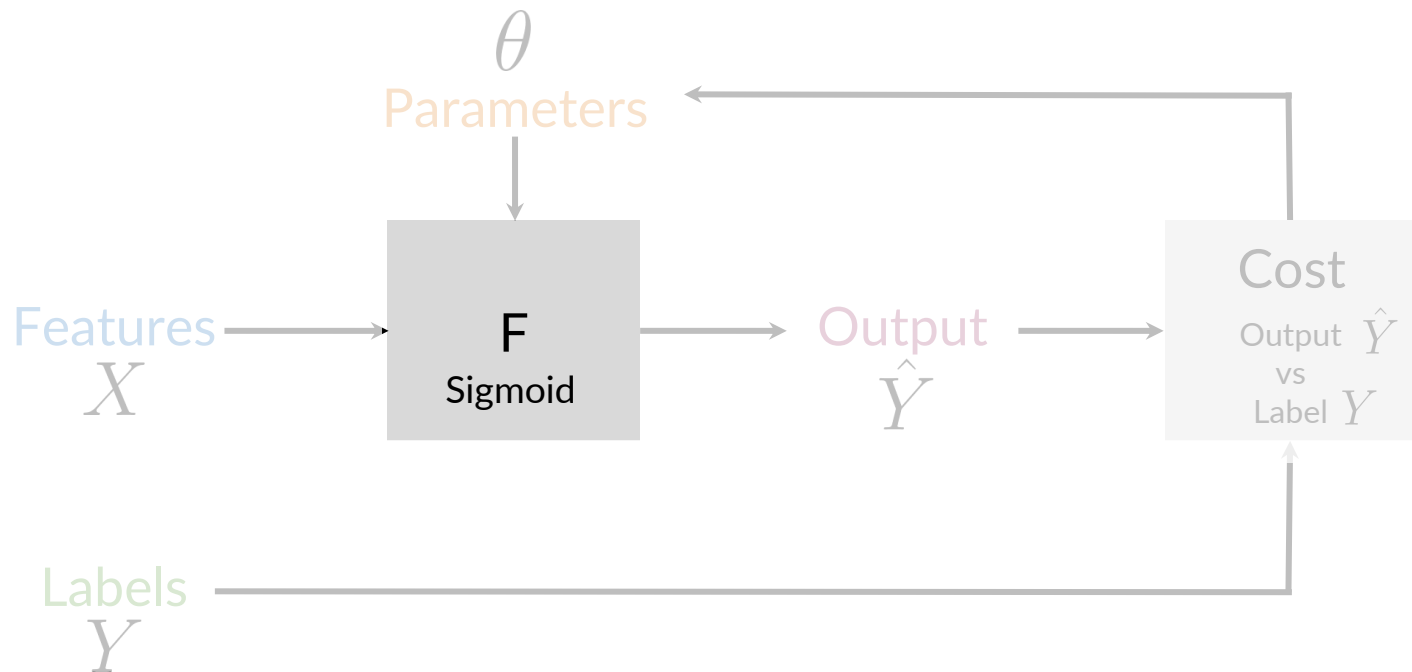
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Logistic Regression Overview

Outline

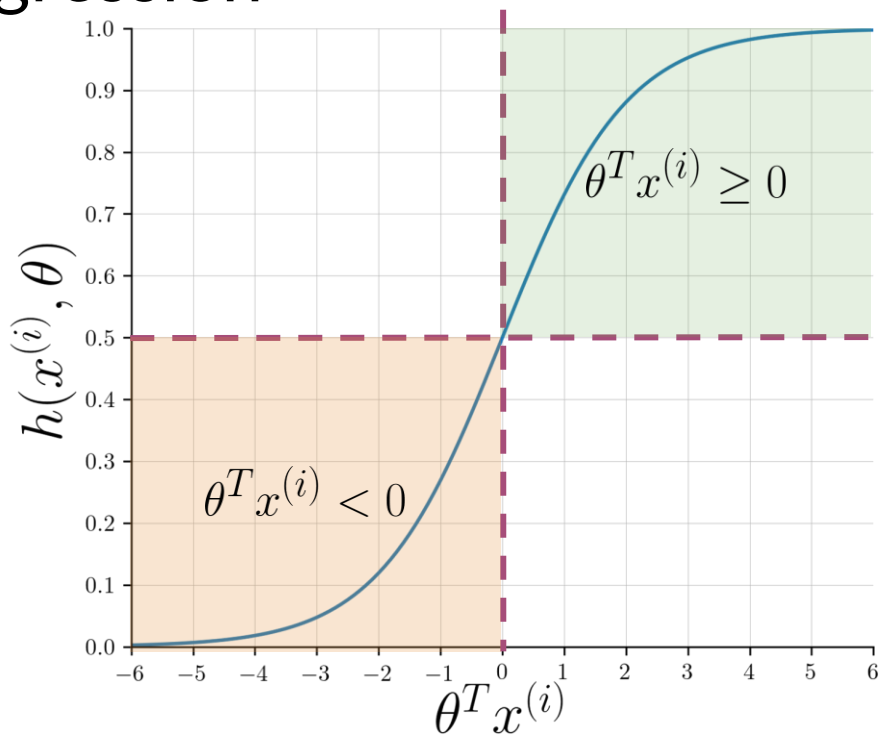
- Supervised learning and logistic regression
- Sigmoid function

Overview of logistic regression



Overview of logistic regression

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

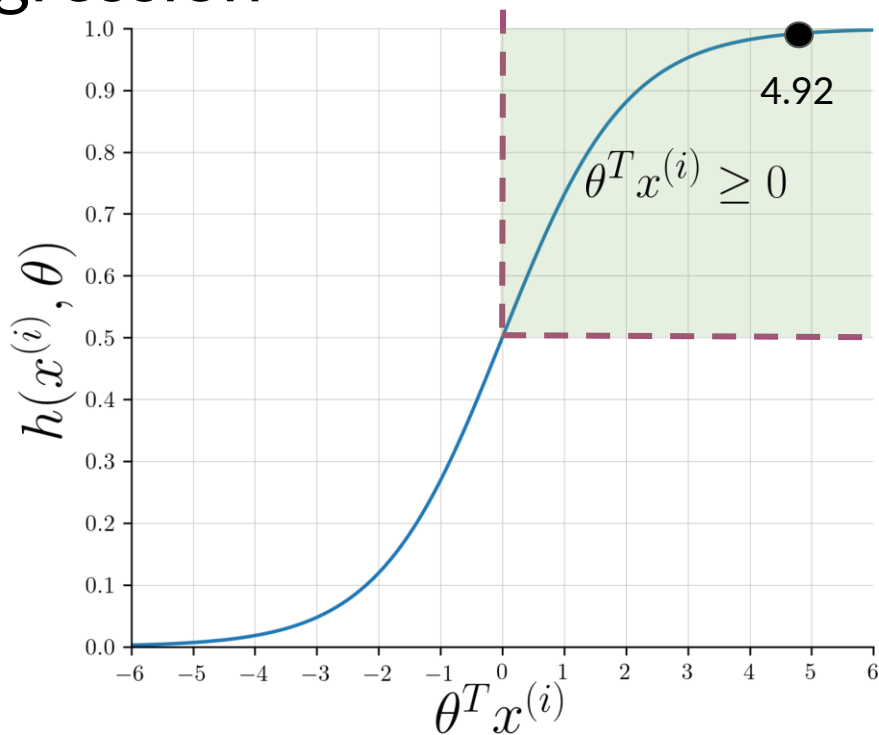


Overview of logistic regression

@YMourri and
@AndrewYNg are tuning a
GREAT AI model

[tun, ai, great,
model]

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



Summary

- Sigmoid function
- $\theta^T x^{(i)} \geq 0 \longrightarrow h(x^{(i)}, \theta) \geq 0.5$, positive
- $\theta^T x^{(i)} < 0 \longrightarrow h(x^{(i)}, \theta) < 0.5$, negative



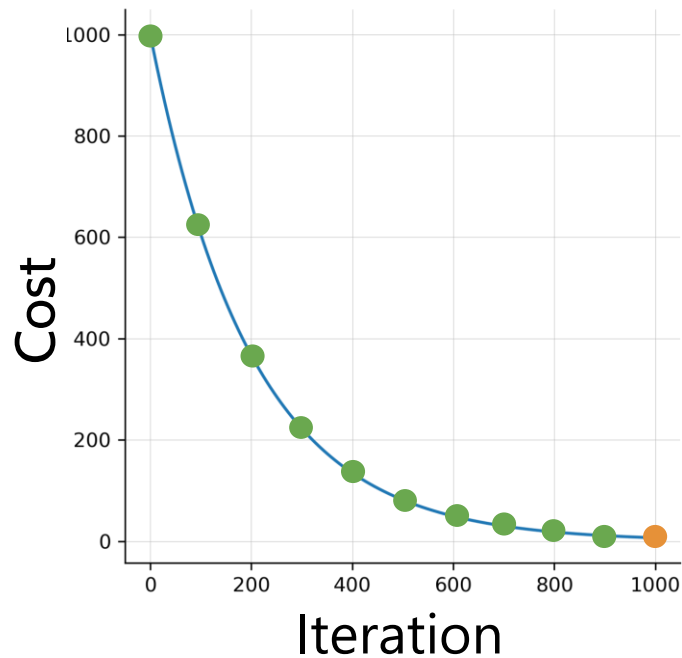
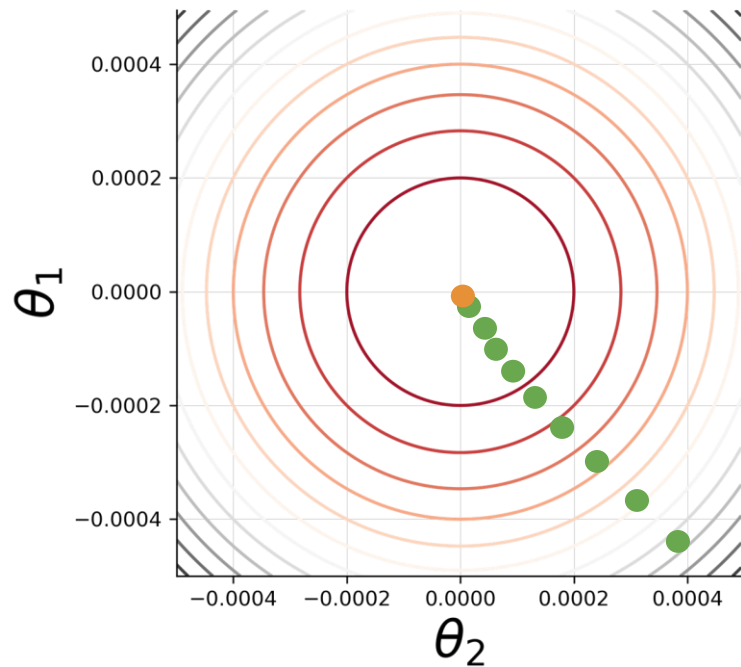
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Logistic Regression: Training

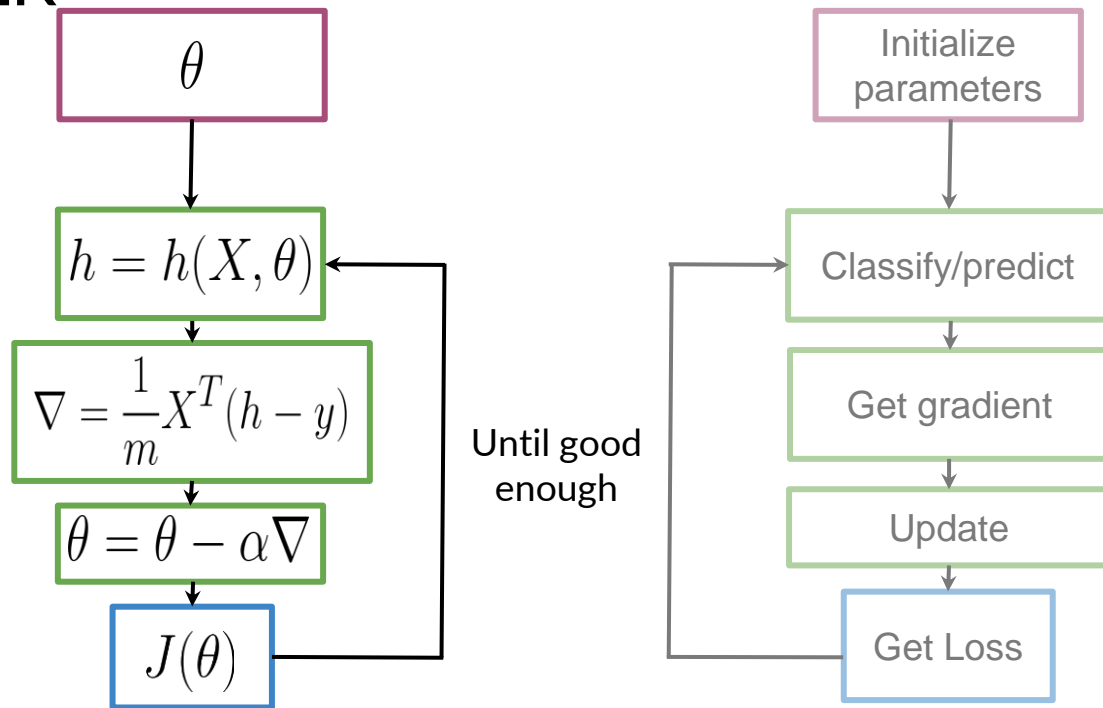
Outline

- Review the steps in the training process
- Overview of gradient descent

Training LR



Training LR



Summary

- Visualize how gradient descent works
 - Use gradient descent to train your logistic regression classifier
- Compute the accuracy of your model



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Logistic Regression: Testing

Outline

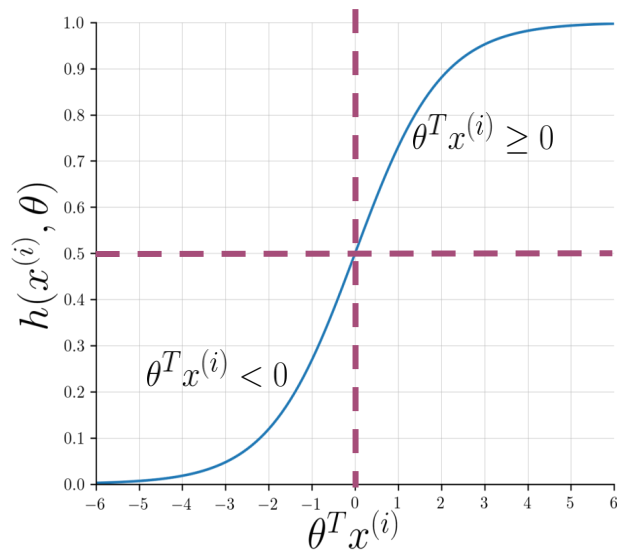
- Using your validation set to compute model accuracy
- What the accuracy metric means

Testing logistic regression

- X_{val} Y_{val} θ

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

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



Testing logistic regression

- X_{val} Y_{val} θ

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

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

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

Testing logistic regression

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

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

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

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

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

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

Testing logistic regression

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

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

$$\text{accuracy} = \frac{4}{5} = 0.8$$

Summary

- $X_{val} \ Y_{val} \longrightarrow$ Performance on unseen data
- Accuracy $\longrightarrow \sum_{i=1}^m \frac{(pred^{(i)} == y_{val}^{(i)})}{m}$

To improve model: step size, number of iterations, regularization, new features, etc.



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Logistic Regression: Cost Function

Outline

- Overview of the logistic cost function, AKA the binary cross-entropy function

Cost function for logistic regression

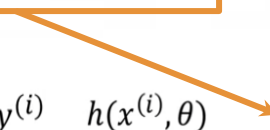
$$J(\theta) = -\frac{1}{m} \sum_{i=1}^m [y^{(i)} \log h(x^{(i)}, \theta) + (1 - y^{(i)}) \log(1 - h(x^{(i)}, \theta))]$$

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


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



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

Cost function for logistic regression

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



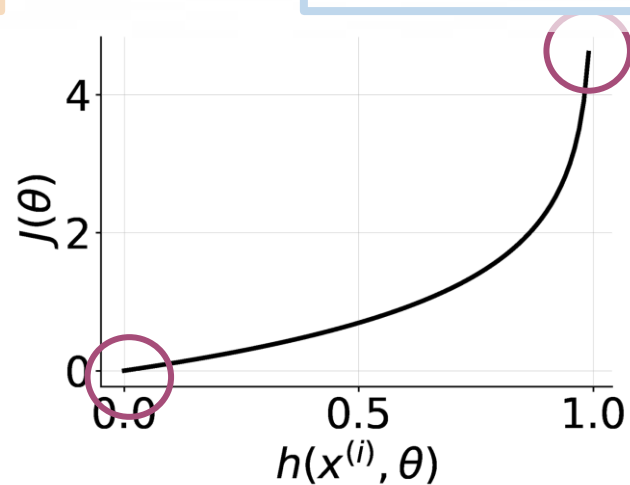
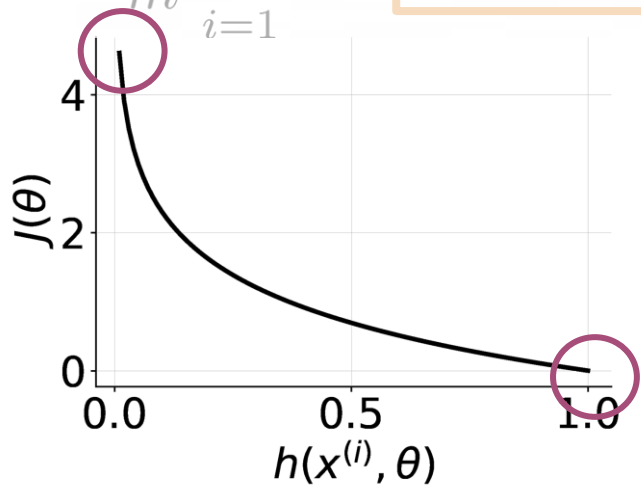
$y^{(i)}$	$h(x^{(i)}, \theta)$	
1	any	0
0	0.01	~0
0	~1	-inf

Cost function for logistic regression

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

Cost function for logistic regression

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



Summary

- Strong disagreement = high cost
- Strong agreement = low cost
- Aim for the lowest cost!