# INTRODUCTION TO DATA SCIENCE

This lecture is based on course by E. Fox and C. Guestrin, Univ of Washington

WFAiS UJ, Informatyka Stosowana I stopień studiów

## Classification

An inteligent restaurant review system

It's a big day & I want to book a table at a nice Japanese restaurant



## What is a sentiment of the review



#### Positive reviews not positive about everything

#### Sample review:

Watching the chefs create incredible edible art made the <u>experience</u> very unique.

My wife tried their <u>ramen</u> and it was pretty forgettable.

All the <u>sushi</u> was delicious! Easily best <u>sushi</u> in Seattle.







## Topic sentiments

### From reviews to topic sentiments



Novel intelligent restaurant review app



## Inteligent restaurant review system

# All reviews for restaurant



# Break all reviews into sentences

The seaweed salad was just OK, vegetable salad was just ordinary.

I like the interior decoration and the blackboard menu on the wall.

All the sushi was delicious.

My wife tried their ramen and it was pretty forgettable.

The sushi was amazing, and the rice is just outstanding.

The service is somewhat hectic.

Easily best sushi in Seattle.

## Core building block

Easily best sushi in Seattle.



## Sentence Sentiment Classifier





## Inteligent restaurant review system

## All reviews for restaurant

This is probably my favorite place to eat Japanese in Seattle. My boyfriend and foreignd right of scaliop, Japanese snappor (seasonal), and the agodash tofu and 2 special rolls. Boyfriend and is repealed rolls, because the right and seahmi cuts is where this place excets. The tofu, as recommended by other Velebran was maraing. It's more chewy and the sauce/grany is the perfect amount of flavor for the delicate tofu.

\*\*Dring here at the sush bar made me feel like sitting front row to an amazing performance. We didn't have reeos, barged down to the ID after work, got here breathlessly at 5.10pm, and got the last two seats in the place.

\*\*Comment of the last two seats in the place.\*\*

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\*\*Comment of the last two seats in the place.\*\*

\*\*Comment of the last two seats in the place.\*\*

\*\*Comment of the last two seats and dishes are small.\*\*

## Break all reviews into sentences

The seaweed salad was just OK, vegetable salad was just ordinary.

I like the interior decoration and the blackboard menu on the wall.

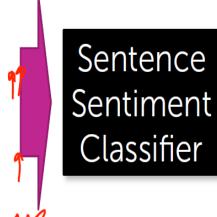
All the sushi was delicious.

My wife tried their ramen and it was pretty forgettable.

The sushi was amazing, and the rice is just outstanding.

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Easily best sushi in Seattle.

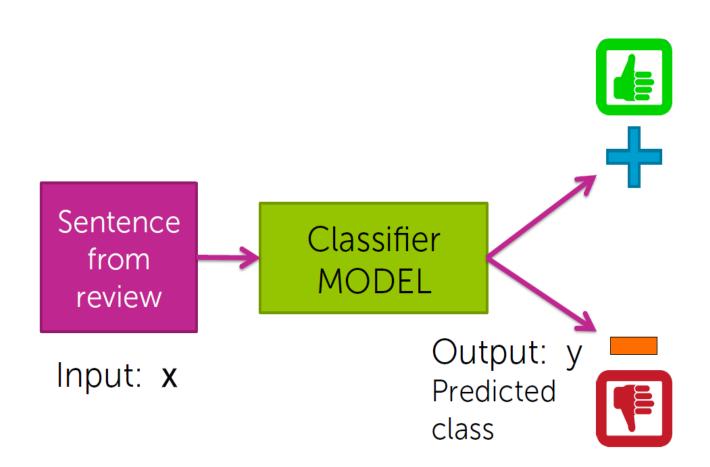


Average predictions



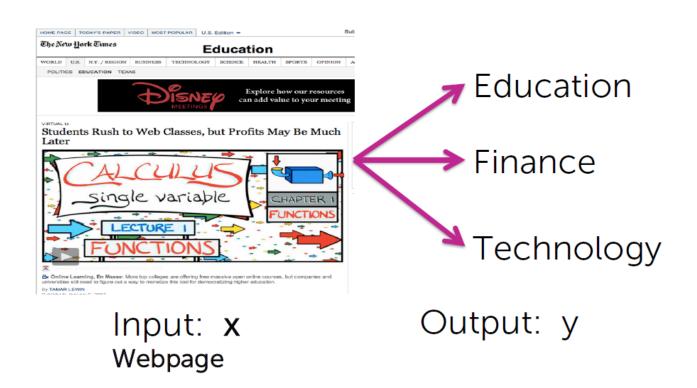


## Classifier



## Multiclass classifier

#### Output y has more than 2 categories

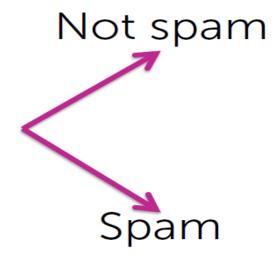


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# Spam filtering



Text of email, sender, IP,...

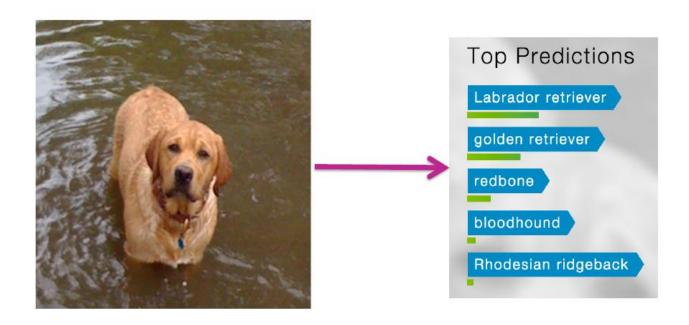


Output: y

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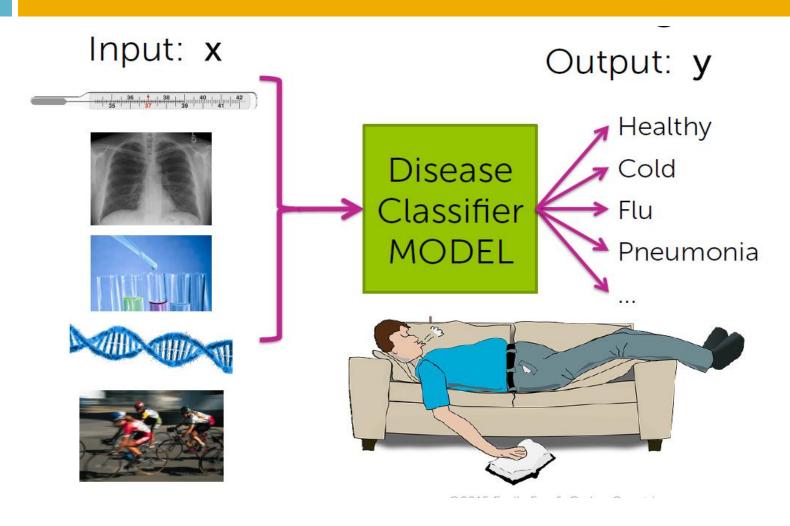
# Image classification



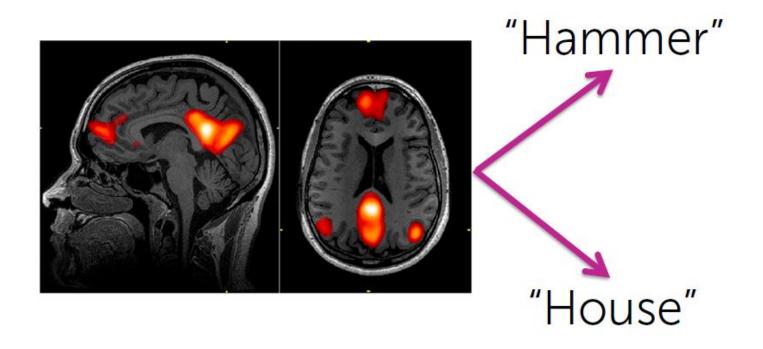
Input: **x** Image pixels

Output: y
Predicted object

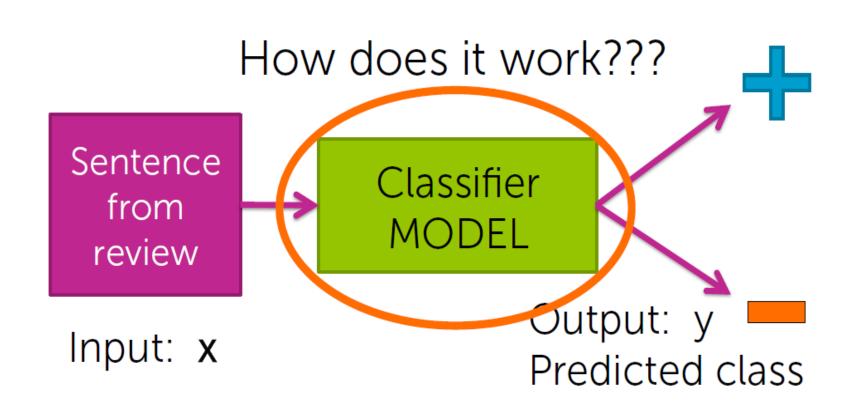
## Personalized medical diagnosis



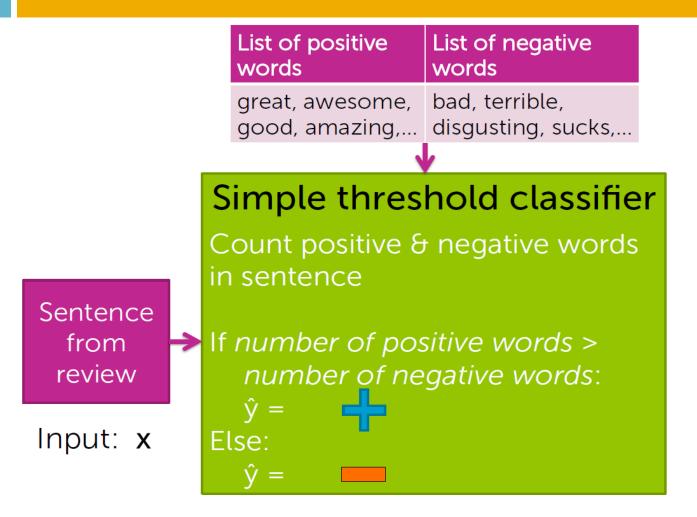
# Reading your mind



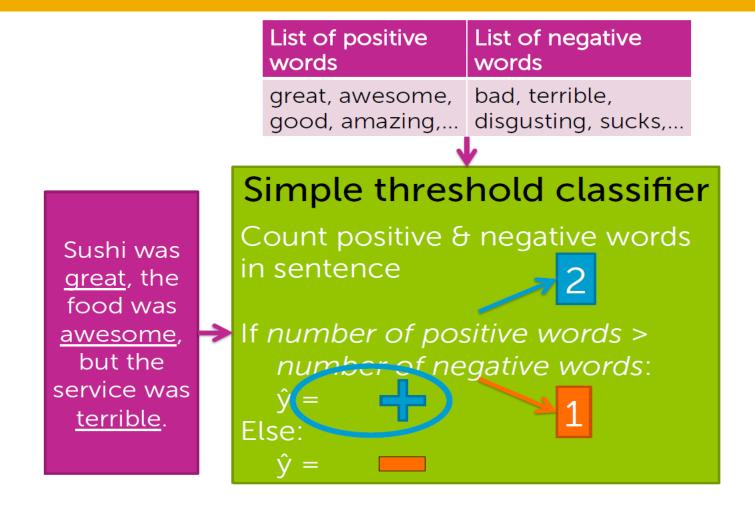
## Representing classifiers



## Simple threshold classifier



## Simple threshold classifier



## Problems with threshold classifier

- How do we get list of positive/negative words?
- Words have different degrees of sentiment:
  - Great > good
  - How do we weigh different words?
- Single words are not enough:
  - Good → Positive
  - Not good → Negative

Addressed by learning a classifier

Addressed by more elaborate features

# A (linear) classifier

Will use training data to learn a weight for each word

Word	Weight
good	1.0
great	1.5
awesome	2.7
bad	-1.0
terrible	-2.1
awful	-3.3
restaurant, the, we, where,	0.0
•••	

## Scoring a sentence

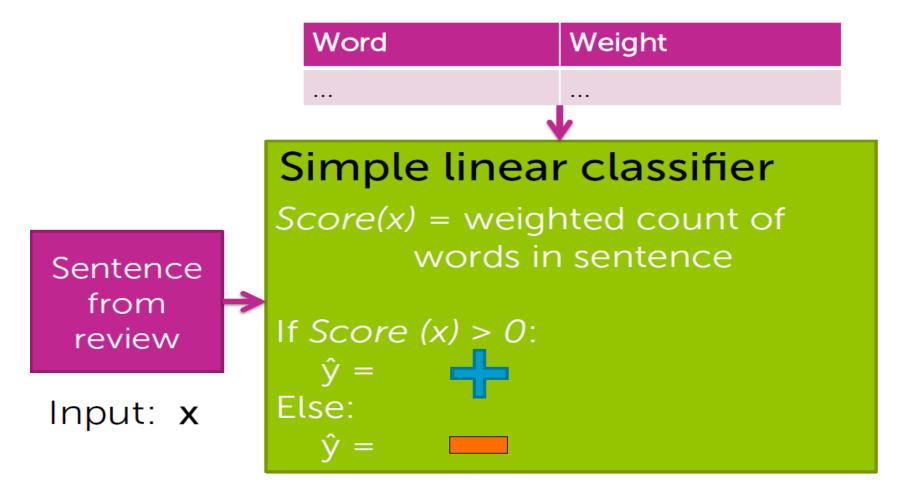
Word	Weight
good	1.0
great	1.2
awesome	<u>1.</u> 7
bad	-1.0
terrible	- <u>2.1</u>
awful	-3.3
restaurant, the, we, where,	0.0

#### Input x:

Sushi was <u>great</u>, the food was <u>awesome</u>, but the service was <u>terrible</u>.

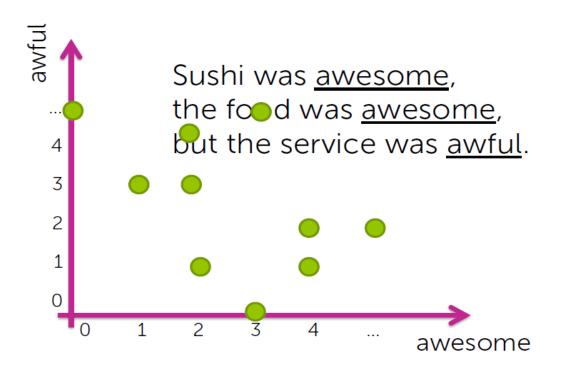
Called a linear classifier, because output is weighted sum of input.

## Simple linear classifier



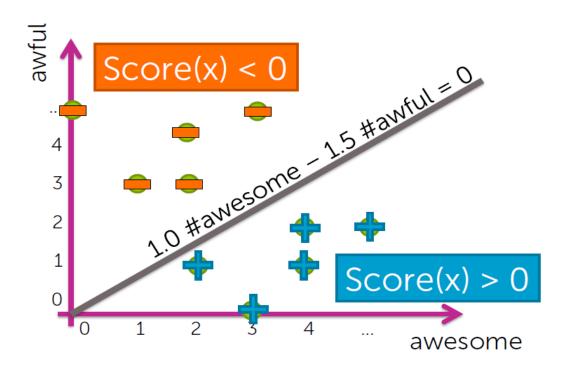
# Suppose only two words had non-zero weight

Word	Weight	
awesome	1.0	Score(x) = 1.0 #awesome - 1.5 #awful
awful	-1.5	Score(x) 1.0 havesome 1.0 haviat



## Decision boundary example

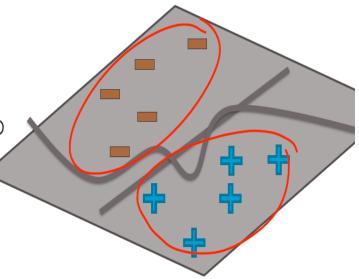
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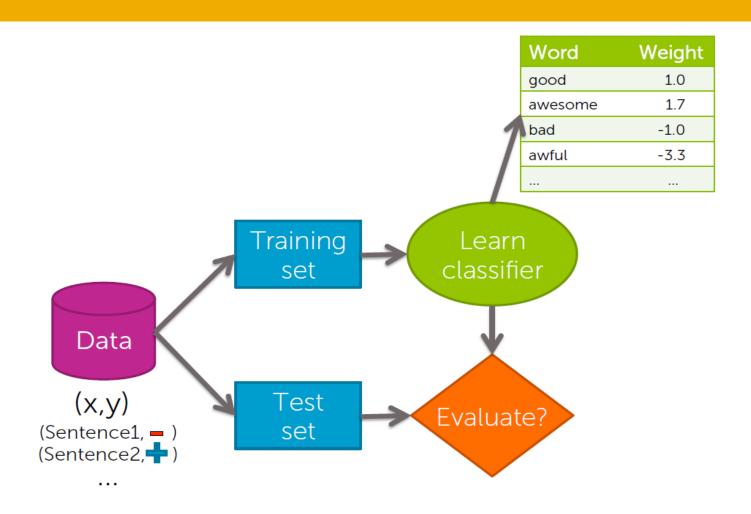
## Decision boundary

#### Separates positive & negative predictions

- For linear classifiers:
  - When 2 weights are non-zero
    - → line
  - When 3 weights are non-zero
    - → plane
  - When many weights are non-zero
    - → hyperplane
- For more general classifiers
  - → more complicated shapes



## Training a classifier = Learning the weights



# Classification error & accuracy

Error measures fraction of mistakes

- Best possible value is 0.0
- Often, measure accuracy
  - Fraction of correct predictions

Best possible value is 1.0

### What if you ignore the sentence and just guess?

- For binary classification:
  - Half the time, you'll get it right! (on average)
    - $\rightarrow$  accuracy = 0.5

- For k classes, accuracy = 1/k
  - 0.333 for 3 classes, 0.25 for 4 classes,...

At the very, very, very least, you should healthily beat random...
Otherwise, it's (usually) pointless...

# Is a classifier with 90% accuracy good? Depends...

2010 data shows: "90% emails sent are spam!"

Predicting every email is spam gets you 90% accuracy!!!

Majority class prediction

Amazing performance when there is class imbalance (but silly approach)

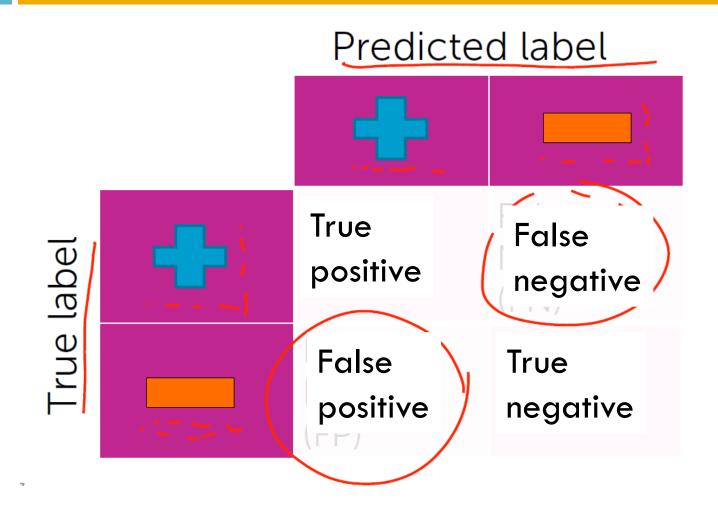
- One class is more common than others
- Beats random (if you know the majority class)

# What is a good accuracy?

# So, always be digging in and asking the hard questions about reported accuracies

- Is there class imbalance?
- How does it compare to a simple, baseline approach?
  - Random guessing
  - Majority class
  - **–** ...
- Most importantly: what accuracy does my application need?
  - What is good enough for my user's experience?
  - What is the impact of the mistakes we make?

# Types of mistakes



## Cost of mistakes

# Cost of different types of mistakes can be different (& high) in some applications

	Spam filtering	Medical diagnosis
False negative	Annoying	Disease not treated
False positive	Email lost Higher Got	Wasteful treatment

## Confusion matrix: binary classification

100 fest examples		Predicted label		
		+		
True label	60	So	10	
True	40	5	35	

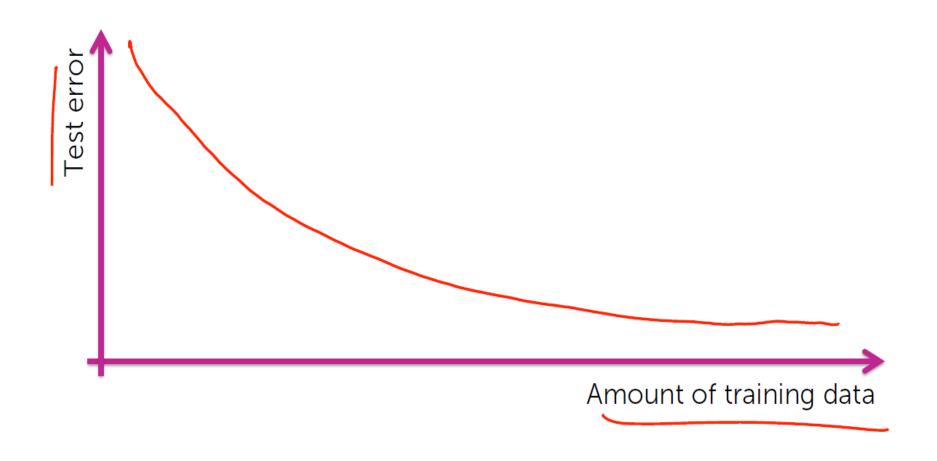
#### Confusion matrix: multiclass classification

100 tes	f examples	Predicted label		
		Healthy	Cold	Flu
<u> </u>	Healthy	60	8	2
True label	Cold 20	4	12	4
<u> </u>	Flu 18	0	2	8

#### How much data does a model need to learn?

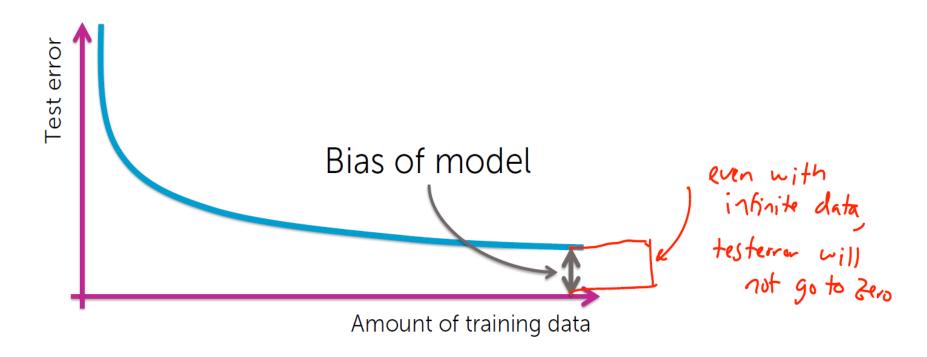
- The more the merrier ©
  - But data quality is most important factor
- Theoretical techniques sometimes can bound how much data is needed
  - Typically too loose for practical application
  - But provide guidance
- In practice:
  - More complex models require more data
  - Empirical analysis can provide guidance

# Learning curves



## Learning curves

Is there a limit? Yes, for most models...



#### More complex models tend to have less bias...

Sentiment classifier using single words can do OK, but...

Never classifies correctly: "The sushi was not good."

More complex model: consider pairs of words (bigrams)

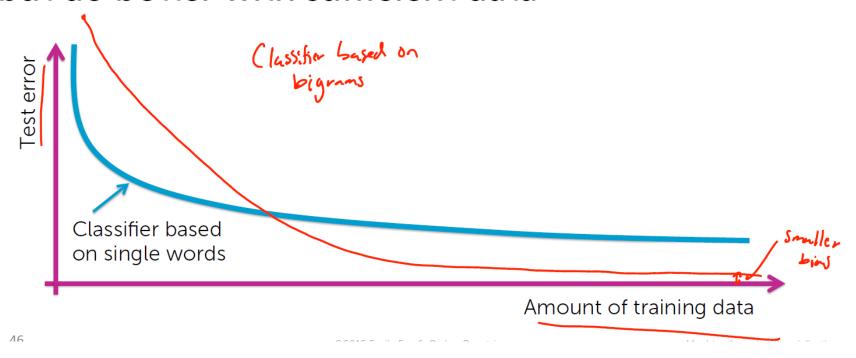
Word	Weight
good	+1.5
not good	-2.1

Less bias → potentially more accurate, needs more data to learn

ΛГ

# Classification based on bigrams

Models with less bias tend to need more data to learn well, but do better with sufficient data



# How confident is your prediction?

Thus far, we've outputted a prediction



- But, how sure are you about the prediction?
  - "The sushi & everything  $\leftarrow$  P(y=+|x) = 0.99 else were awesome!"
    - "The sushi was good, the service was OK." P(y=+|x) = 0.55

Many classifiers provide a confidence level:

Output label

Input sentence

Extremely useful in practice

### We have discussed how to

- Identify a classification problem and some common applications
- Describe decision boundaries and linear classifiers
- Train a classifier
- Measure its error
  - Some rules of thumb for good accuracy
- Interpret the types of error associated with classification
- Describe the tradeoffs between model bias and data set size
- Use class probability to express degree of confidence in prediction