



# Classification: Analyzing Sentiment

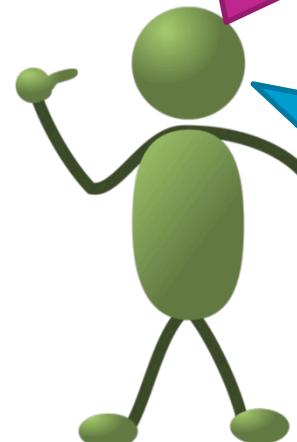


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# Predicting sentiment by topic: *An intelligent restaurant review system*

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

Seattle has many  
★★★★★  
sushi restaurants



What are people  
saying about  
the food?  
the ambiance?...





428 reviews

\$\$ · Japanese, Sushi Bars

# Positive reviews not positive about everything



Experience



Sample review:

Watching the chefs create incredible edible art made the experience very unique.



My wife tried their ramen and it was pretty forgettable.



All the sushi was delicious! Easily best sushi in Seattle.

# From reviews to topic sentiments

All reviews  
for restaurant



7/21/2015

This is probably my favorite place to eat Japanese in Seattle. My boyfriend and I ordered nigiri of scallop, Japanese snapper (seasonal), and the agedashi tofu and 2 special rolls. I would skip the special rolls, because the nigiri and sashimi cuts is where this place excels. The tofu, as recommended by other Yelpers was amazing. It's more chewy and the sauce/gravy is the perfect amount of flavor for the delicate tofu.



6/11/2015

Dining here at the sushi bar made me feel like sitting front row to an amazing performance. We didn't have reservations, banged down to the last ID after work, got here breathlessly at 5:10pm, and got the last two seats in the place.



6/9/2015

I came here having high expectations due to the reviews of this place, but I was bit disappointed. The restaurant is small so do make reservations when you come here. Dishes cost from \$4-26 each and dishes are small.

Novel intelligent  
restaurant review app

Experience  
★★★★★

Ramen  
★★★

Sushi  
★★★★★

Easily best sushi  
in Seattle.

# Intelligent restaurant review system

## All reviews for restaurant

7/21/2015

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6/9/2015

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## 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.

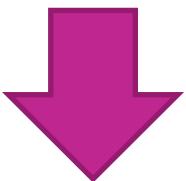
The sushi was amazing, and the rice is just outstanding.

The service is somewhat hectic.

Easily best sushi in Seattle.

# Core building block

Easily best sushi in Seattle.



Sentence Sentiment  
Classifier



Easily best sushi in Seattle.



# Intelligent restaurant review system

All reviews  
for restaurant

★★★★★ 7/21/2015  
This is probably my favorite place to eat Japanese in Seattle. My boyfriend and I ordered nigiri of scallop, Japanese snapper (seasonal), and the agedashi tofu and 2 special rolls. I would skip the special rolls, because the nigiri and sashimi cuts is where this place excels. The tofu, as recommended by other Yelpers was amazing. It's more chewy and the sauce/gravy is the perfect amount of flavor for the delicate tofu.

★★★★★ 8/11/2015  
All the sushi was delicious. Dining here at the sushi bar made me feel like sitting front row to an amazing performance. We didn't have reservations, banged down to the last seat after work, got here breathlessly at 5:10pm, and got the last two seats in the place.

★★★★★ 6/9/2015  
The sushi was amazing, and the rice is just outstanding. The service is just outstanding.

Easily best sushi in Seattle.

Select sentences  
into subtree "sushi"

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

Like the interior decoration and 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.

Sentence  
Sentiment  
Classifier

Average  
predictions

Sushi



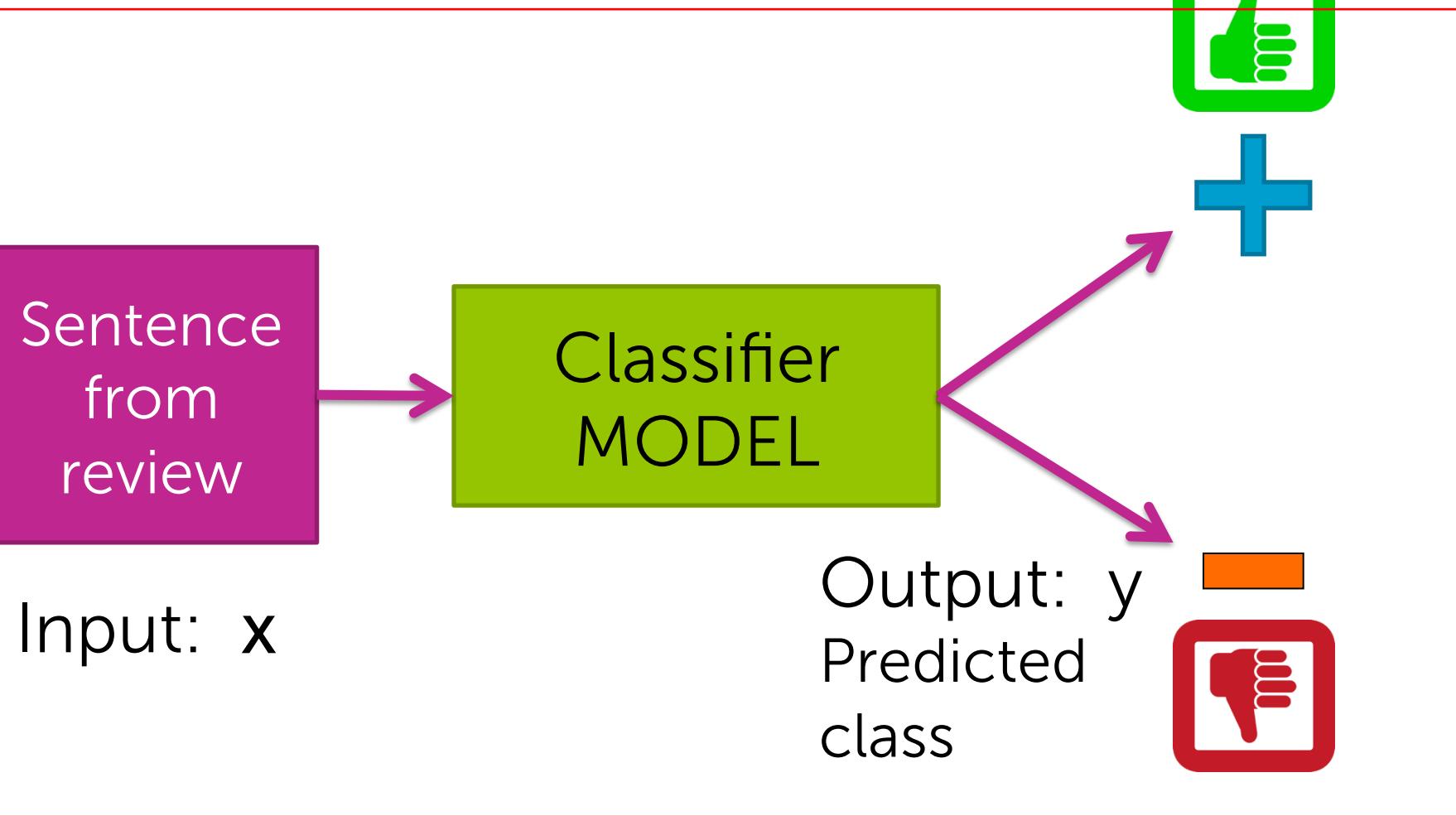
Most



Easily best  
sushi  
in Seattle.

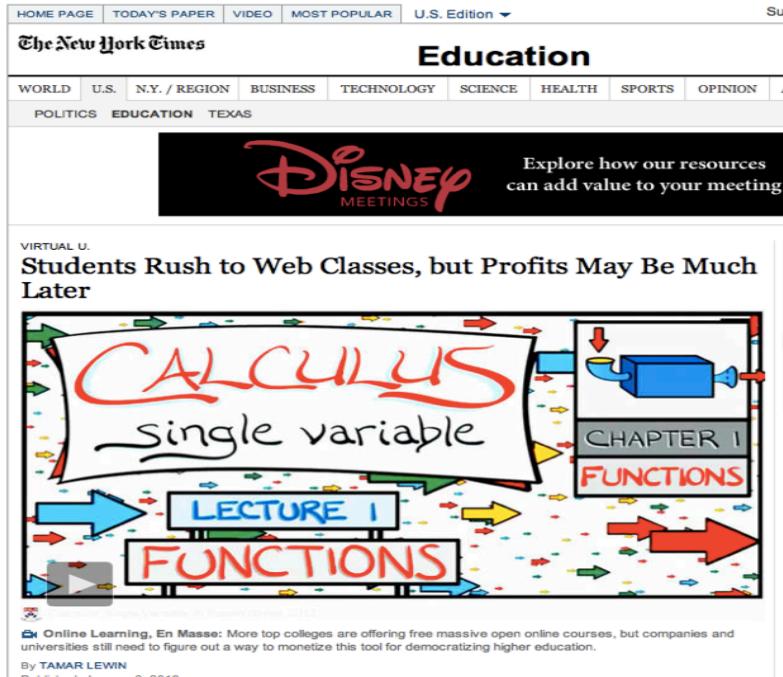
# Classifier applications

# Classifier



# Example multiclass classifier

*Output  $y$  has more than 2 categories*



Input:  $x$   
Webpage

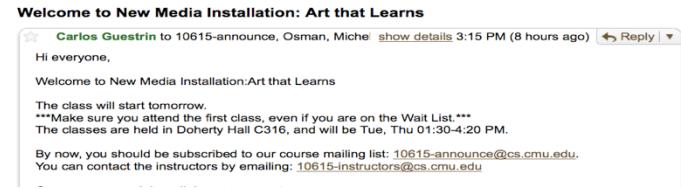
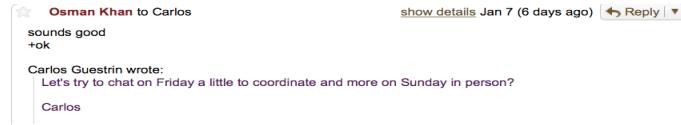
Output:  $y$

Education

Finance

Technology

# Spam filtering



Input: x

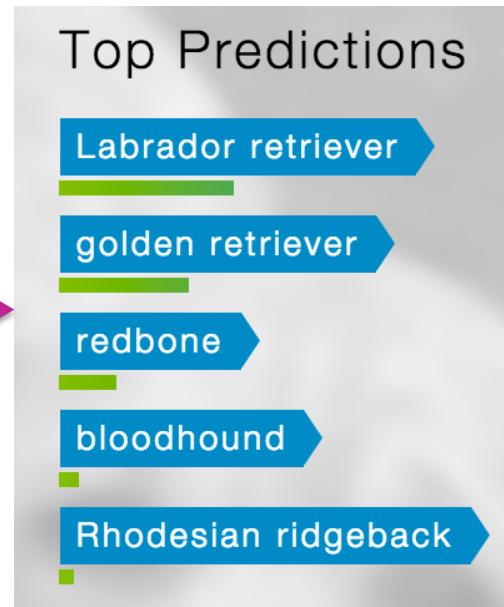
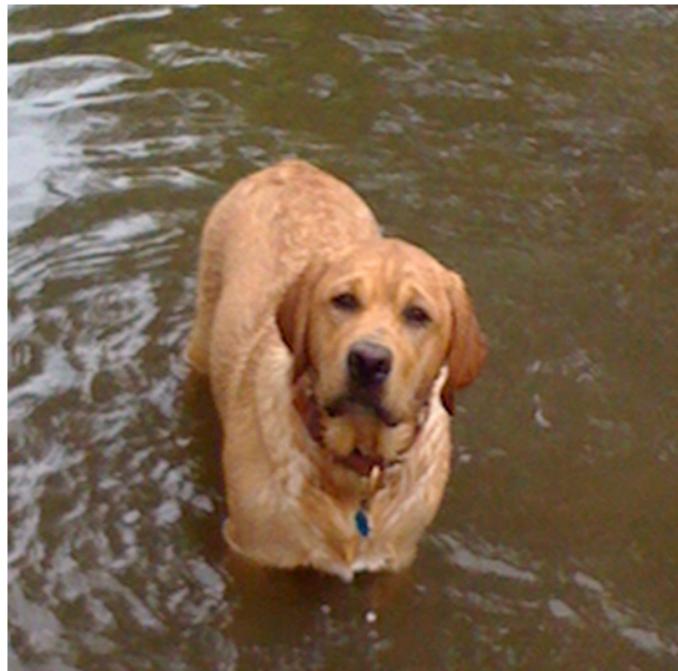
Text of email,  
sender, IP,...

Not spam

Spam

Output: y

# Image classification

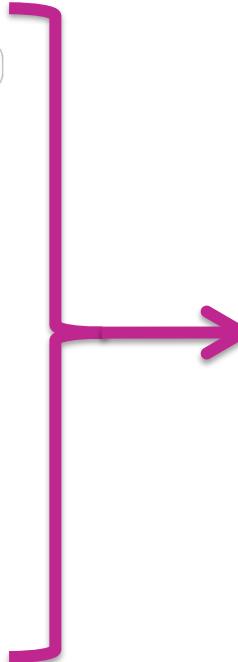


Input:  $x$   
Image pixels

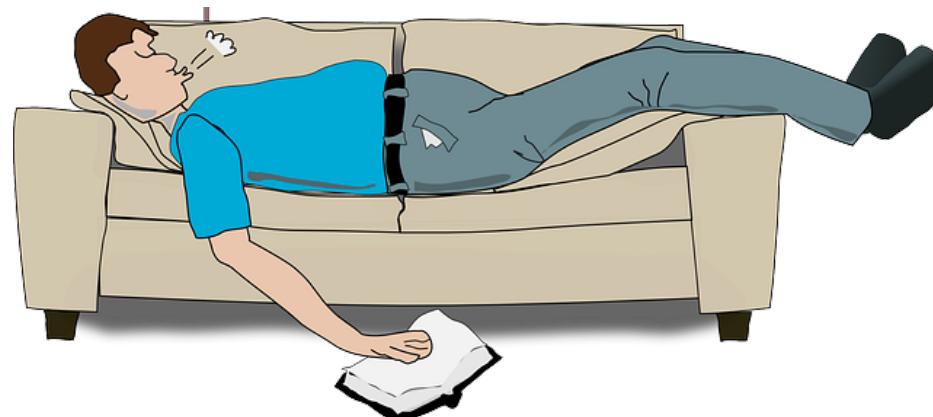
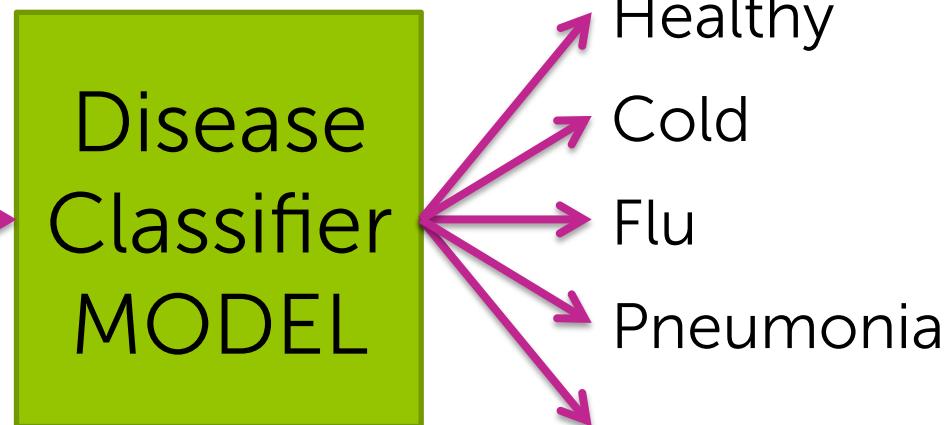
Output:  $y$   
Predicted object

# Personalized medical diagnosis

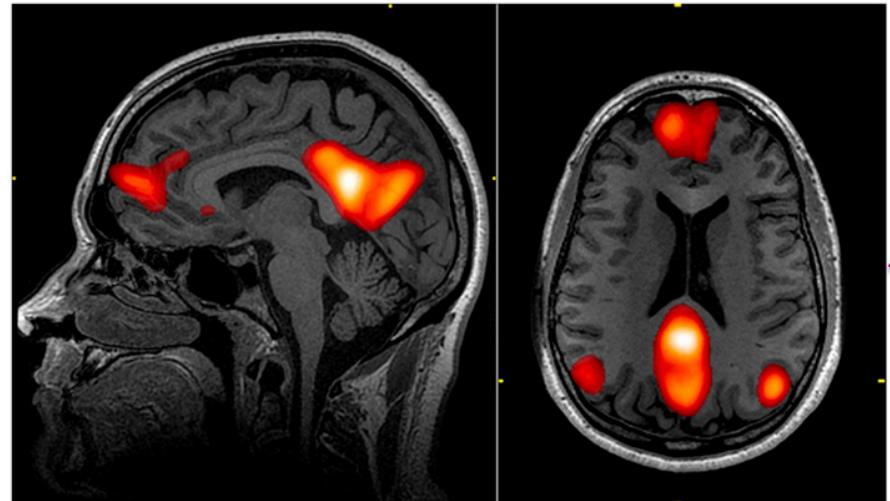
Input:  $x$



Output:  $y$



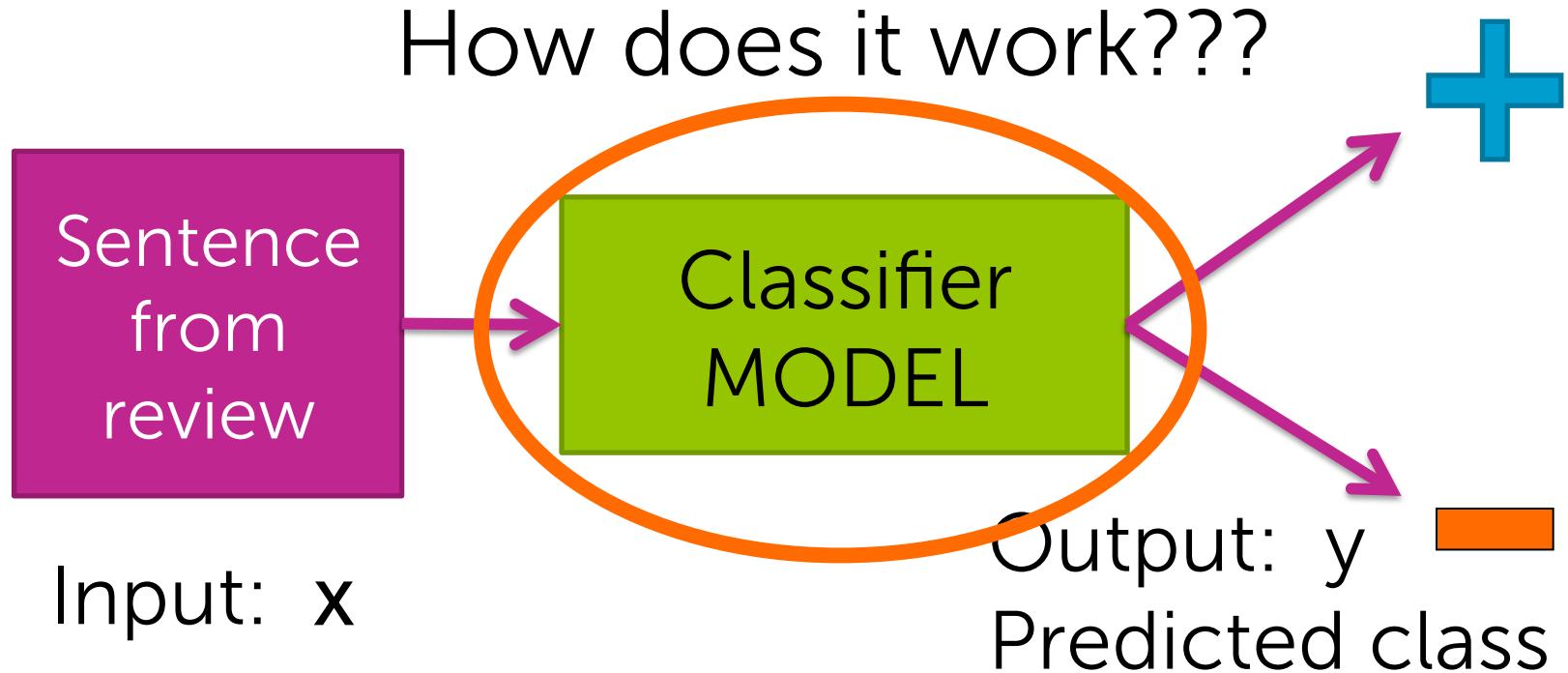
# Reading your mind



“Hammer”  
“House”

# Linear classifiers

# Representing classifiers



List of positive words

great, awesome,  
good, amazing,...

List of negative words

bad, terrible,  
disgusting, sucks,...

Sentence  
from  
review

Input:  $x$

## Simple threshold classifier

Count positive & negative words  
in sentence

If *number of positive words* >  
*number of negative words*:

$$\hat{y} = +$$

Else:

$$\hat{y} = -$$

List of positive words

great, awesome,  
good, amazing,...

List of negative words

bad, terrible,  
disgusting, sucks,...

Sushi was  
great, the  
food was  
awesome,  
but the  
service was  
terrible.

## Simple threshold classifier

Count positive & negative words  
in sentence

2

If *number of positive words* >  
*number of negative words*:

$\hat{y} = +$

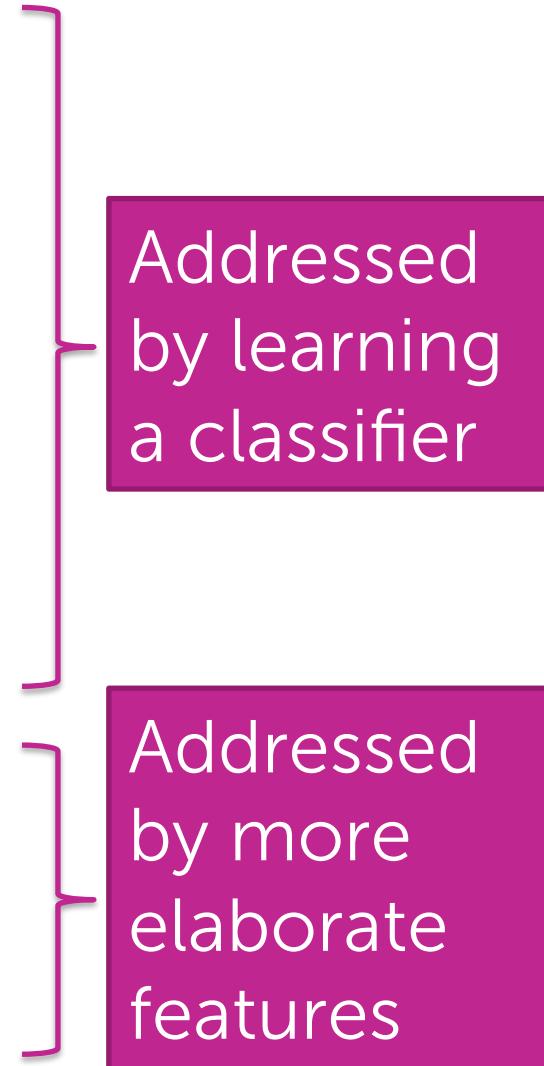
1

Else:

$\hat{y} = -$

# 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



# 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	1.7
bad	-1.0
terrible	-2.1
awful	-3.3
restaurant, the, we, where, ...	0.0
...	...

Input  $x$ :

Sushi was great,  
the food was awesome,  
but the service was terrible.

$$\begin{aligned} \text{Score}(x) &= 1.2 + 1.7 - 2.1 \\ &= 0.8 \end{aligned}$$

$\text{Score}(x) > 0 \Rightarrow +$

if

$\text{Score}(x) < 0 \Rightarrow -$

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

Word	Weight
...	...

Sentence  
from  
review

Input:  $x$

## Simple linear classifier

$\text{Score}(x)$  = weighted count of  
words in sentence

If  $\text{Score}(x) > 0$ :

$$\hat{y} = \begin{matrix} + \\ + \\ + \end{matrix}$$

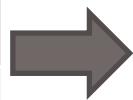
Else:

$$\hat{y} = \begin{matrix} - \\ - \\ - \end{matrix}$$

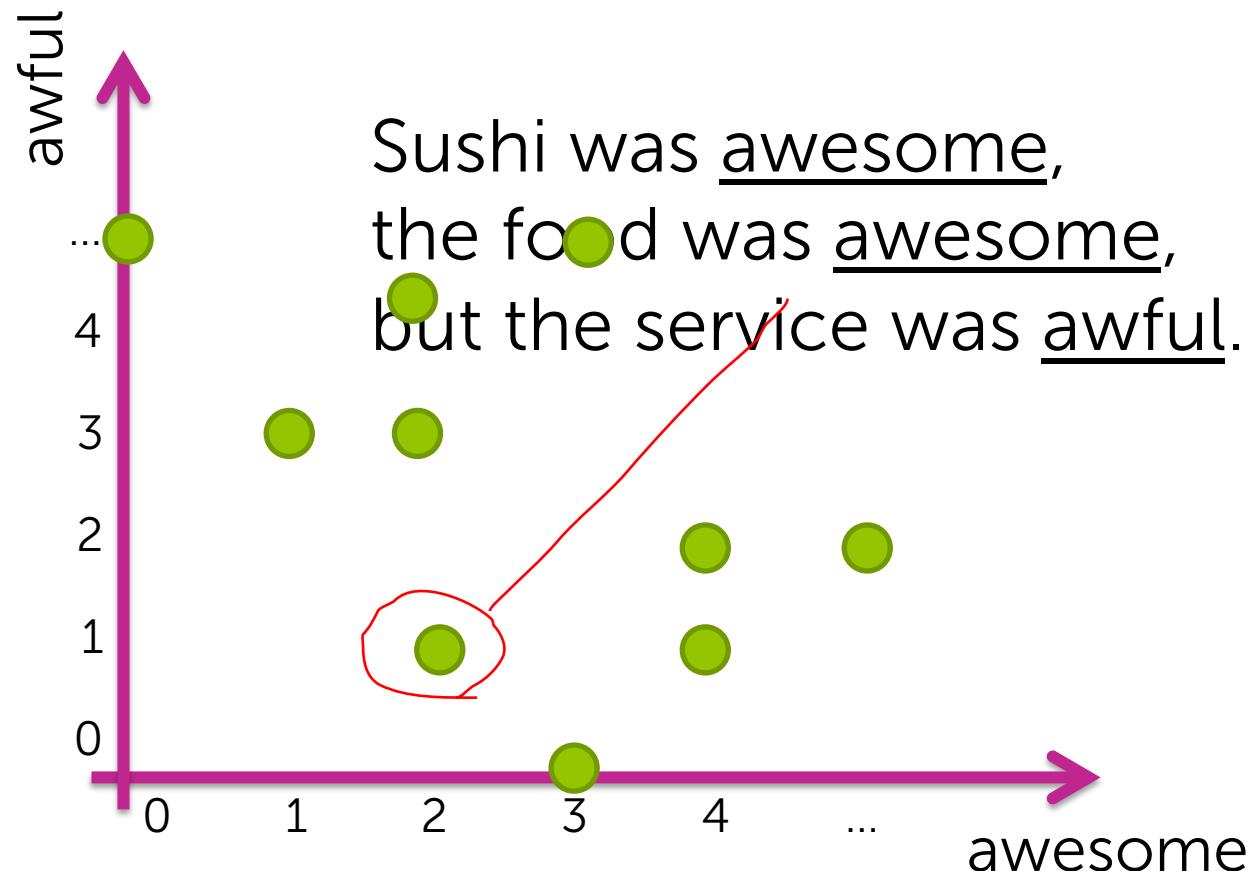
# Decision boundaries

# Suppose only two words had non-zero weight

Word	Weight
awesome	1.0
awful	-1.5



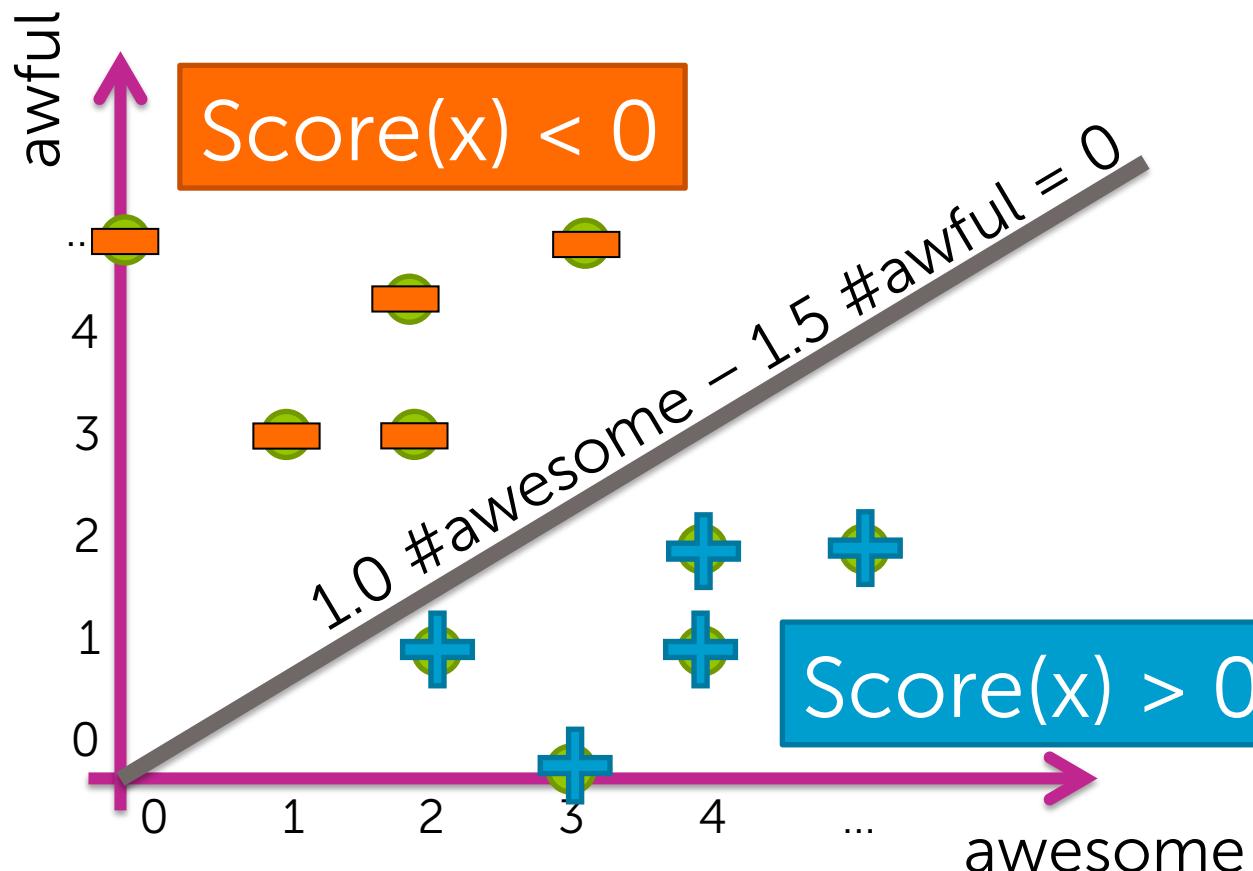
$$\text{Score}(x) = 1.0 \# \text{awesome} - 1.5 \# \text{awful}$$



# Decision boundary example

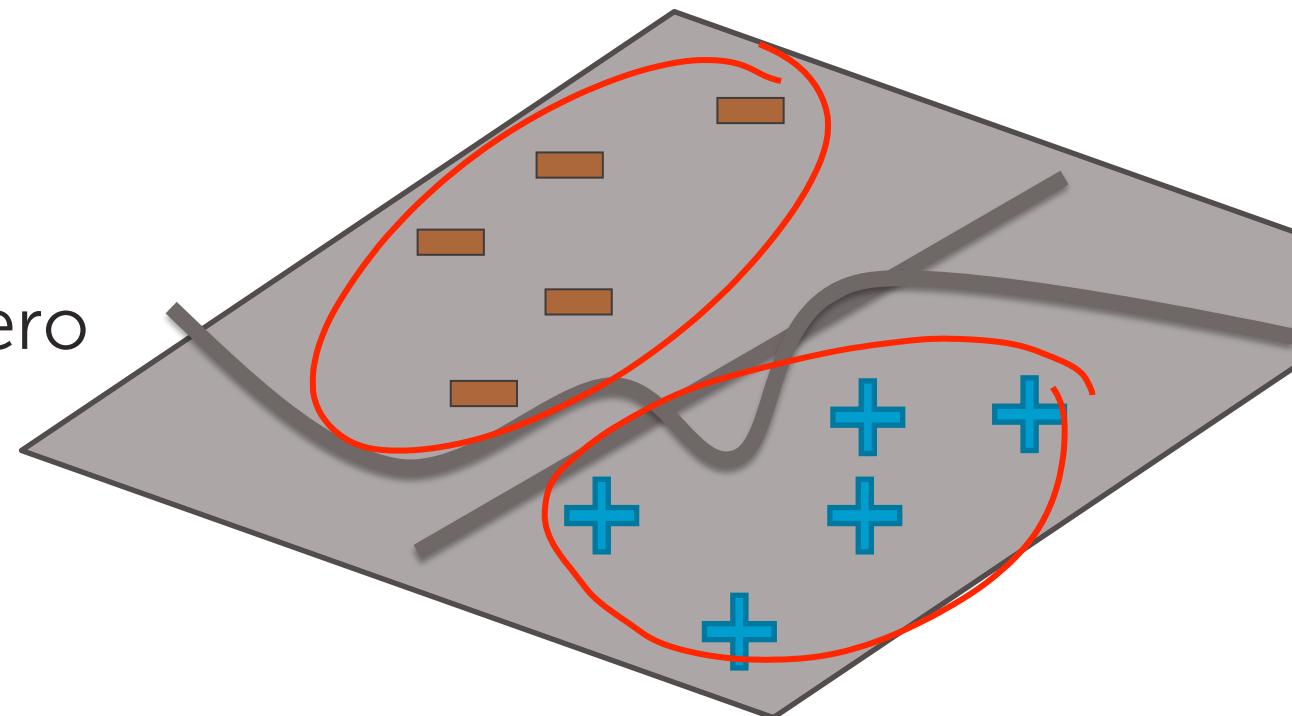
Word	Weight
awesome	1.0
awful	-1.5

$$\rightarrow \text{Score}(x) = 1.0 \# \text{awesome} - 1.5 \# \text{awful}$$



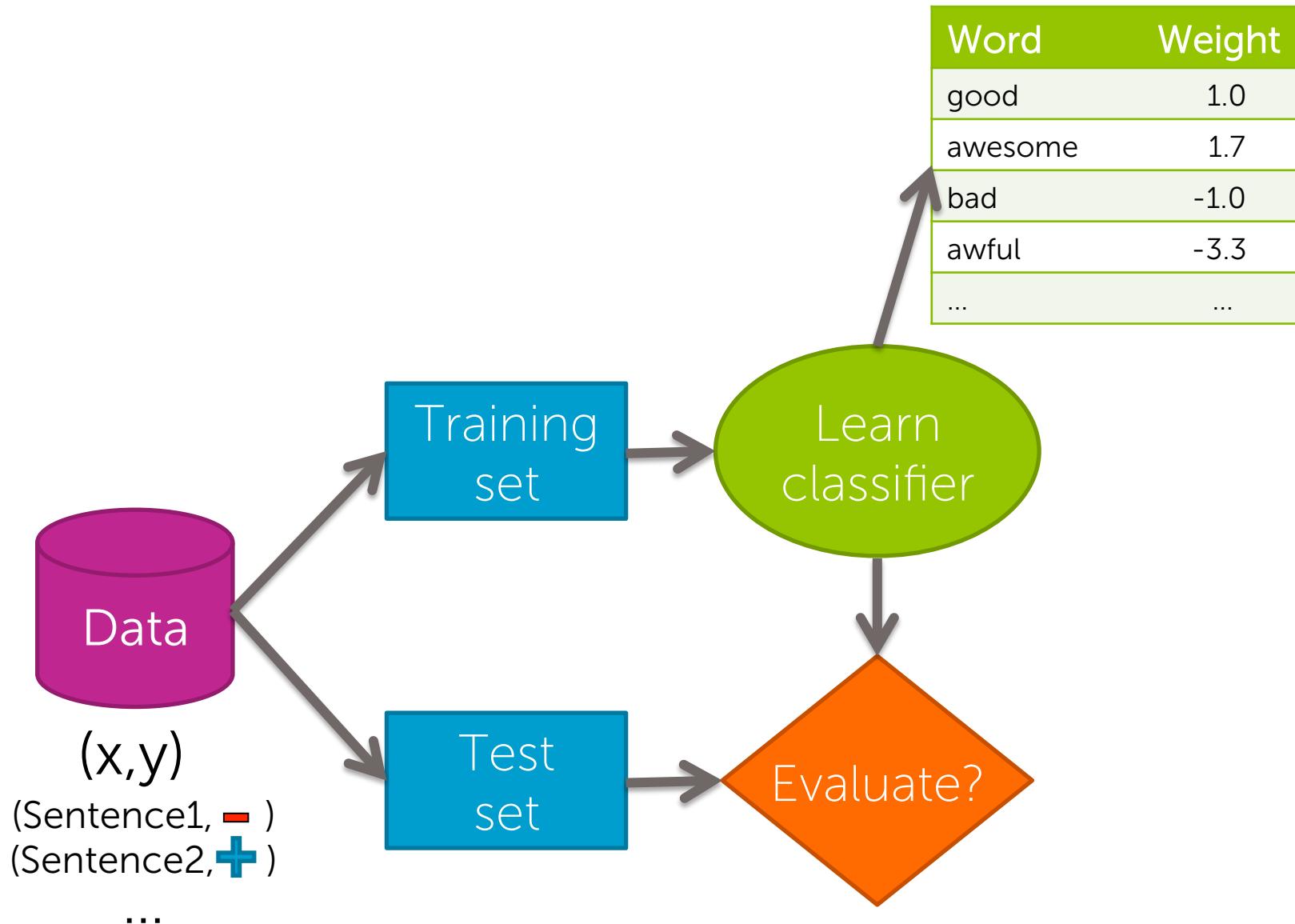
# Decision boundary separates positive & negative predictions

- 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 and evaluating a classifier

# Training a classifier = Learning the weights



# Classification error

Learned classifier

$$\hat{y} = +$$

Test example

(\$Eusbidwasgreat, +)

Mistake!

Correct  
Mistakes

0

0

Hide label

# Classification error & accuracy

- Error measures fraction of mistakes

$$\text{error} = \frac{\text{\# of mistakes}}{\text{Total \# of sentences}}$$

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

$$\text{accuracy} = \frac{\text{\# of correct}}{\text{Total \# of sentences}}$$

- Best possible value is 1.0

# What's a good accuracy?

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

- For binary classification:
  - Half the time, you'll get it right! (on average)  
→ 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)

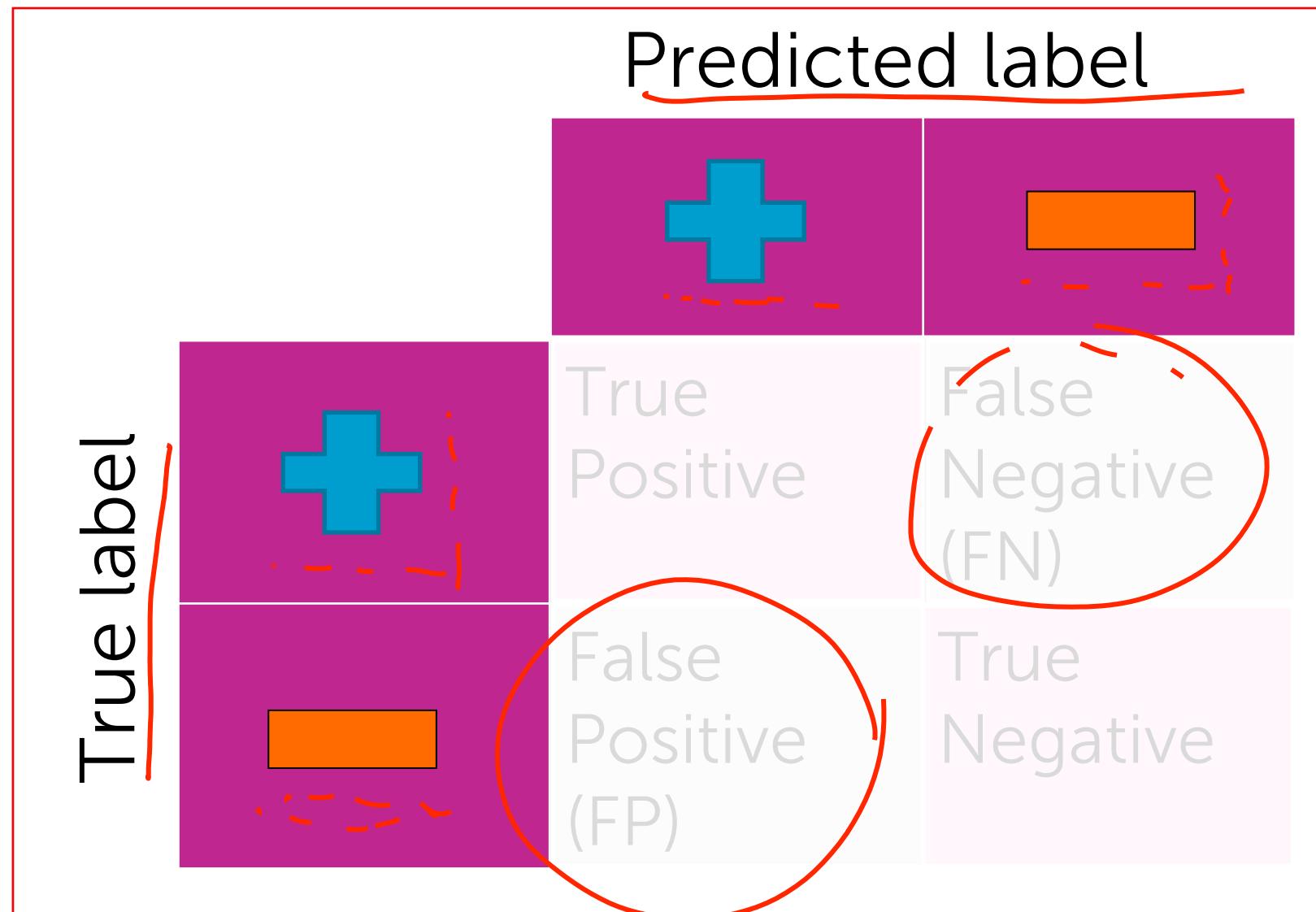
- One class is more common than others
- Beats random (if you know the majority class)

# 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?

# False positives, false negatives, and confusion matrices

# Types 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 <i>Higher cost</i>	Wasteful treatment

# Confusion matrix – binary classification

100 test examples

		Predicted label	
		+	-
True label	+	60	10
	-	5	35

$$\text{accuracy} = \frac{85}{100} = 0.85$$

---

# Confusion matrix – multiclass classification

100 test examples

True label	Predicted label		
	Healthy	Cold	Flu
Healthy	60	8	2
Cold	4	12	4
Flu	0	2	8

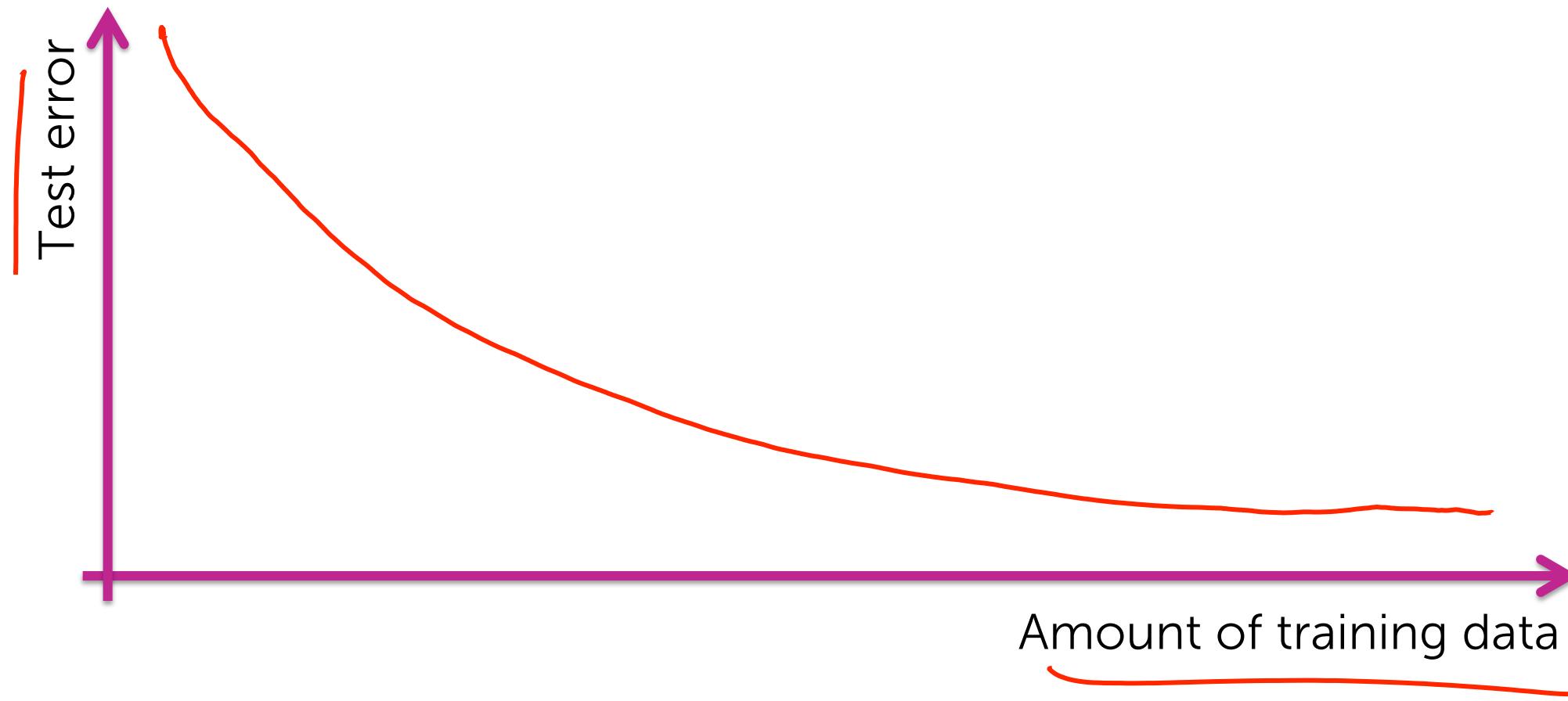
$$\text{accuracy} = \frac{80}{100} = 0.8$$

# Learning curves: *How much data do I need?*

# How much data does a model need to learn?

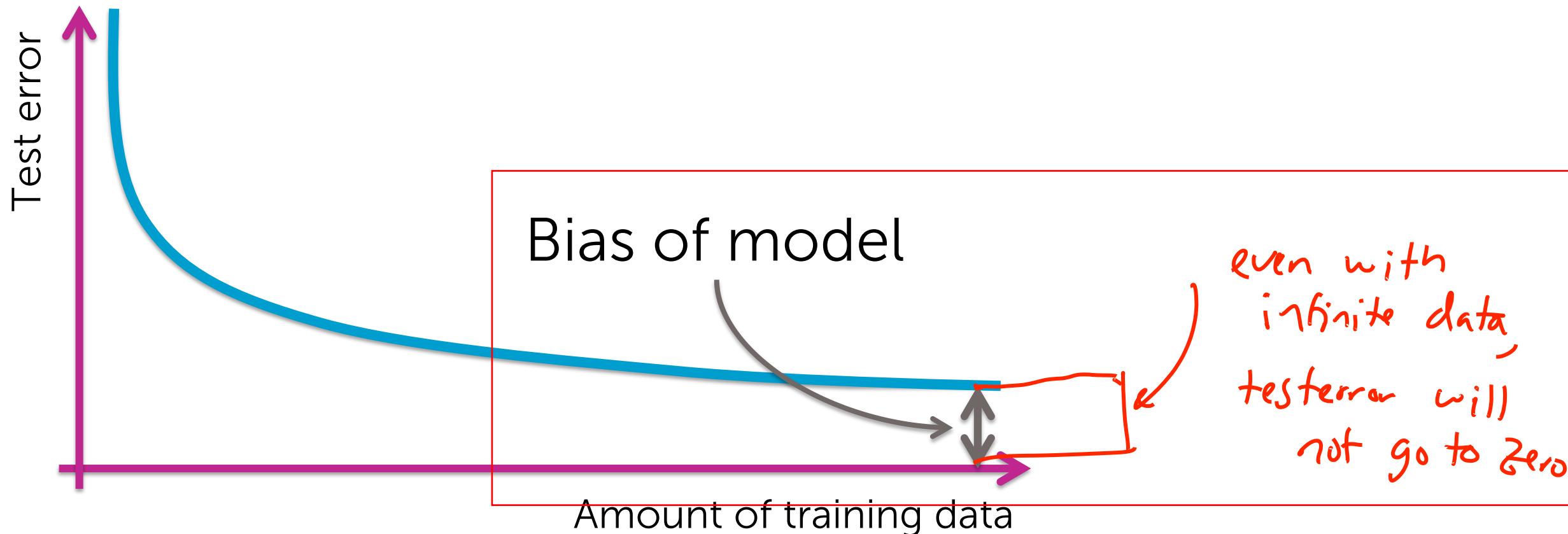
- The more the merrier ☺
  - But data quality is most important factor
- Theoretical techniques sometimes can bound how much data is needed
  - Typically too loose for practical application
  - But provide guidance
- In practice:
  - More complex models require more data
  - Empirical analysis can provide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

# Learning curves



# 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.”



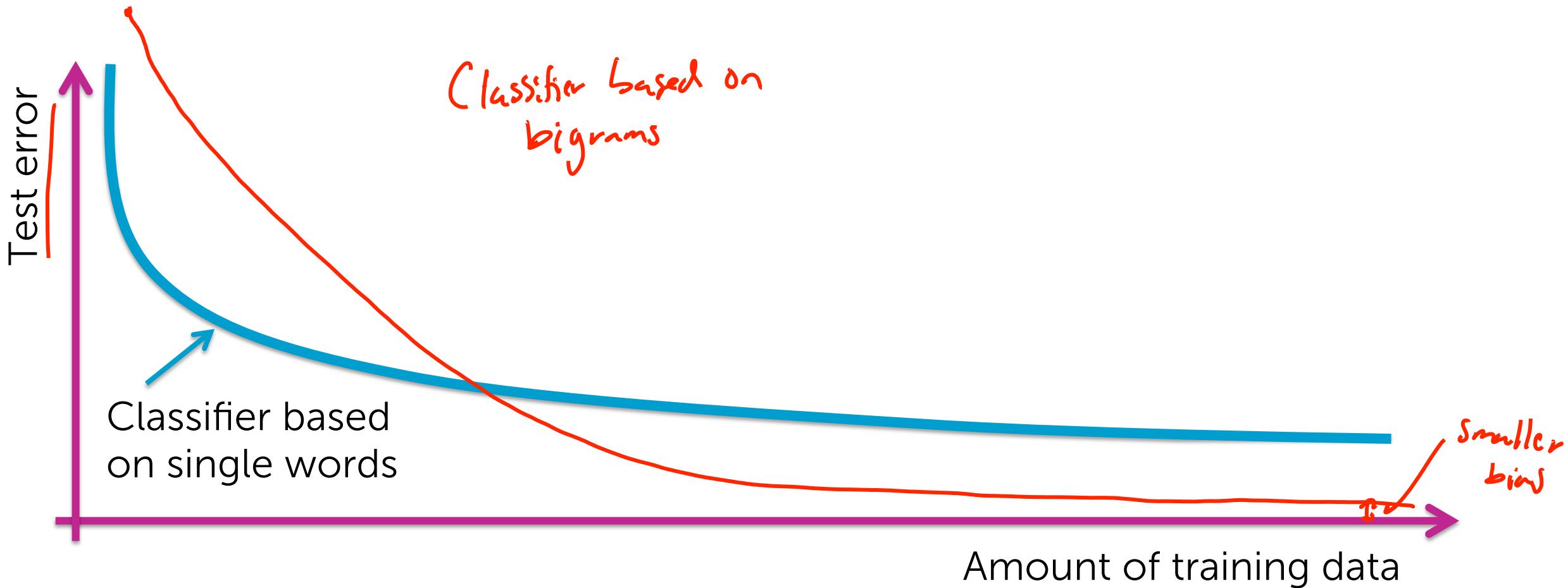
More complex model:  
consider pairs of words (bigrams)

Word	Weight
good	+1.5
not good	-2.1



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

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



# Class probabilities

# How confident is your prediction?

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

Many classifiers provide a confidence level:

$$P(y|x)$$

Output label

Input sentence

Extremely useful in practice

# Summary of classification

# What you can do now...

- 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