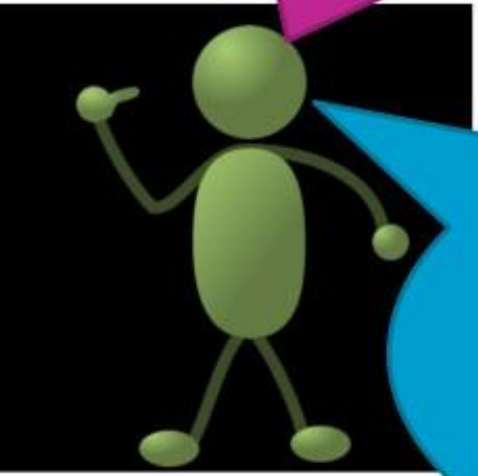
Classification:

Analyzing Sentiment

Utkarsh Kulshrestha

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?...

Positive reviews not positive about everything

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.

Experience

From reviews to topic sentiments

Intelligent 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.

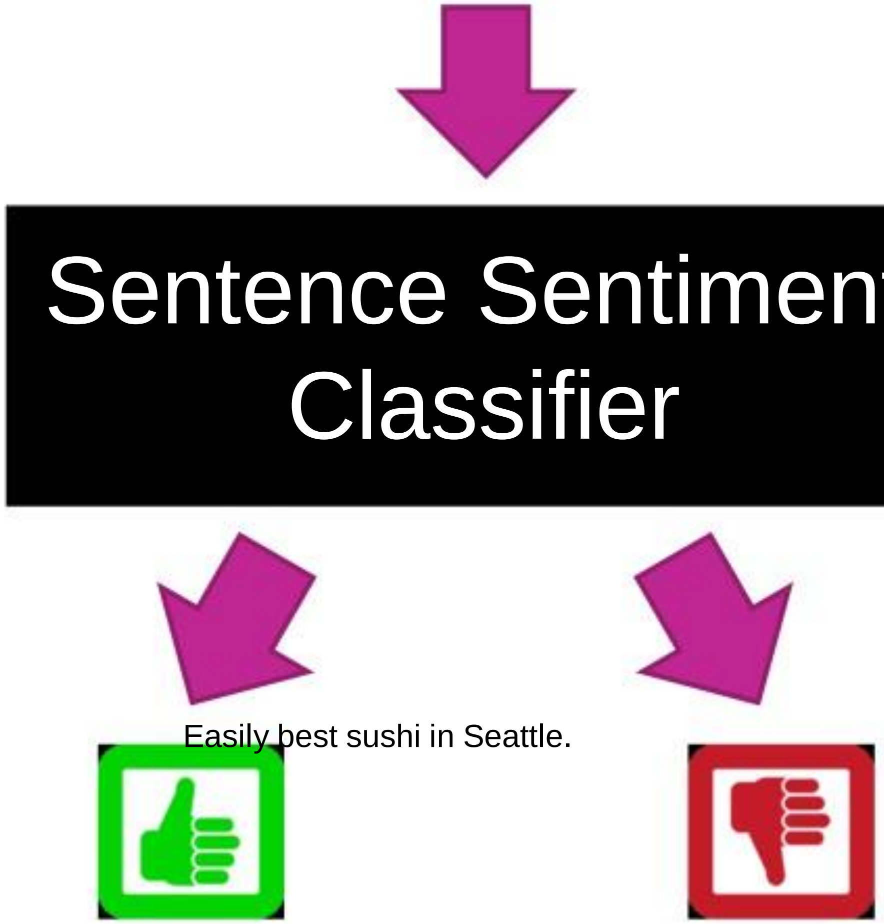
The sushi was amazing, and
the rice is just outstanding.

The service is somewhat hectic.

Easily best sushi in Seattle.

Core building block

Easily best sushi in Seattle.



Intelligent restaurant review system

All reviews
for restaurant

All the sushi was delicious.

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

Easily best sushi in Seattle.

BreaSelect sentences
into sabout “sushi”

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.

Sentence
Sentiment
Classifier

Average
predictions

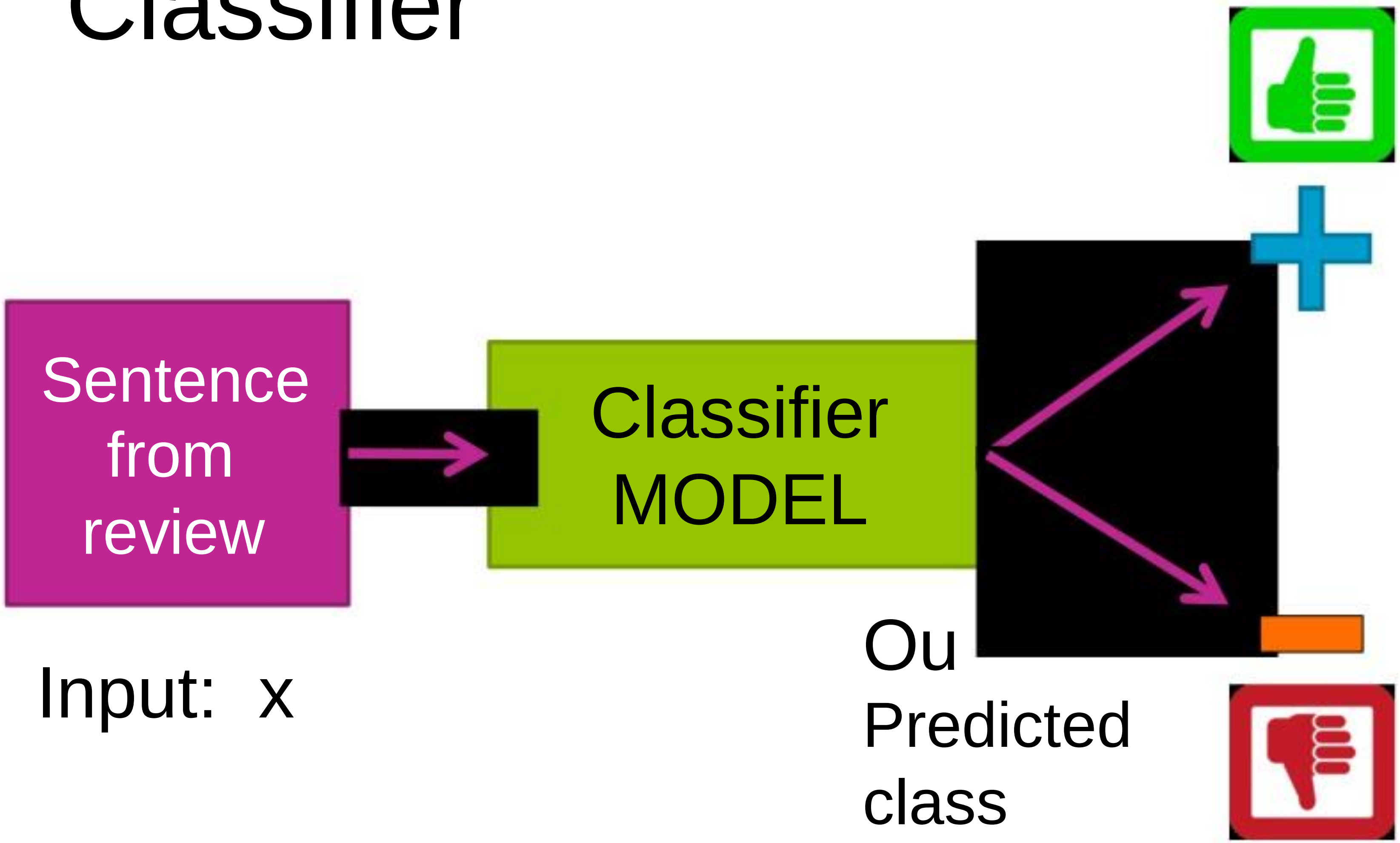
Sushi
★★★★★

Most
&

Easily best
sushi
in Seattle.

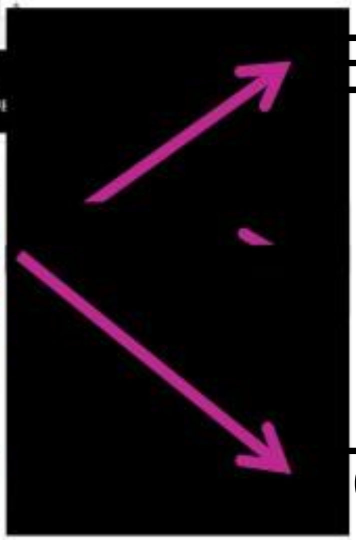
Classifier applications

Classifier


Sentence from review
Classifier MODEL
Input: x
Ou
Predicted class

Example multiclass classifier

Output y has more than 2 categories



Education

Finance

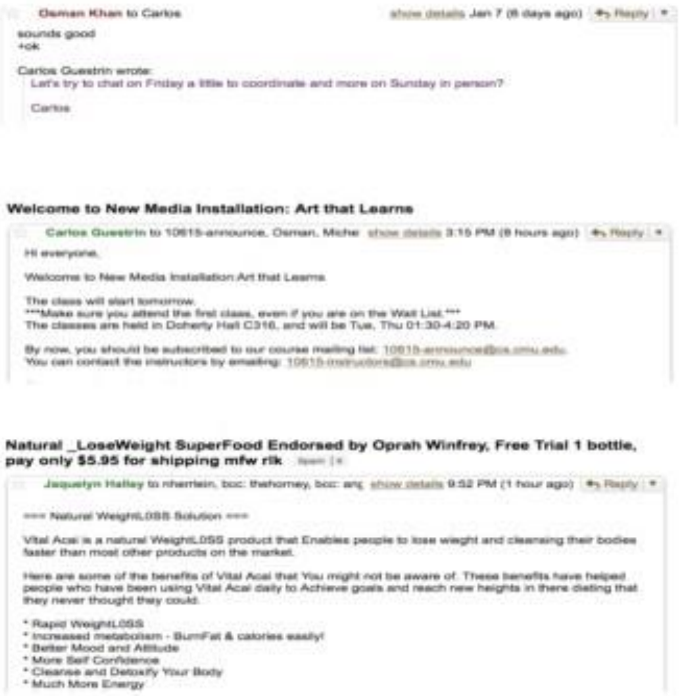
Technology

Input: x

Webpage

Output: y

Spam filtering



Osman Khan to Carlos — show details Jan 7 (6 days ago) Reply

sounds good
+ok

Carlos Guestrin wrote:
Let's try to chat on Friday a little to coordinate and more on Sunday in person?

Carlos

Welcome to New Media Installation: Art that Learns

Carlos Guestrin to 10615-announce, Osman, Miche — show details 3:15 PM (8 hours ago) Reply

Hi everyone,

Welcome to New Media Installation:Art that Learns

The class will start tomorrow.
Make sure you attend the first class, even if you are on the Wait List.
The classes are held in Doherty Hall C316, and will be Tue, Thu 01:30-4:20 PM.

By now, you should be subscribed to our course mailing list: 10615-announce@cs.cmu.edu.
You can contact the instructors by emailing: 10615-instructors@cs.cmu.edu

Natural _LoseWeight SuperFood Endorsed by Oprah Winfrey, Free Trial 1 bottle, pay only $5.95 for shipping mfw rlk

Jaquelyn Halley to nherrlein, bcc: thehorney, bcc: ang — show details 9:52 PM (1 hour ago) Reply

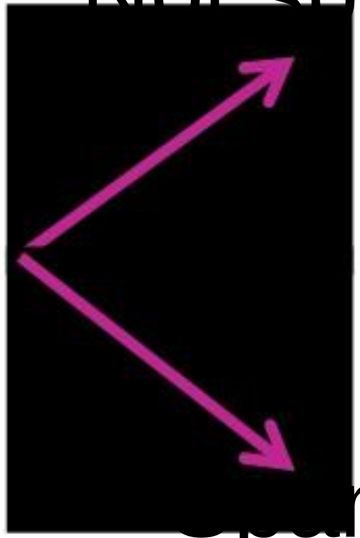
=== Natural WeightLOSS Solution ===

Vital Acai is a natural WeightLOSS product that Enables people to lose wieght and cleansing their bodies faster than most other products on the market.

Here are some of the benefits of Vital Acai that You might not be aware of. These benefits have helped people who have been using Vital Acai daily to Achieve goals and reach new heights in there dieting that they never thought they could.

* Rapid WeightLOSS
* Increased metabolism - BurnFat & calories easily!
* Better Mood and Attitude
* More Self Confidence
* Cleanse and Detoxify Your Body
* Much More Energy

Not spam



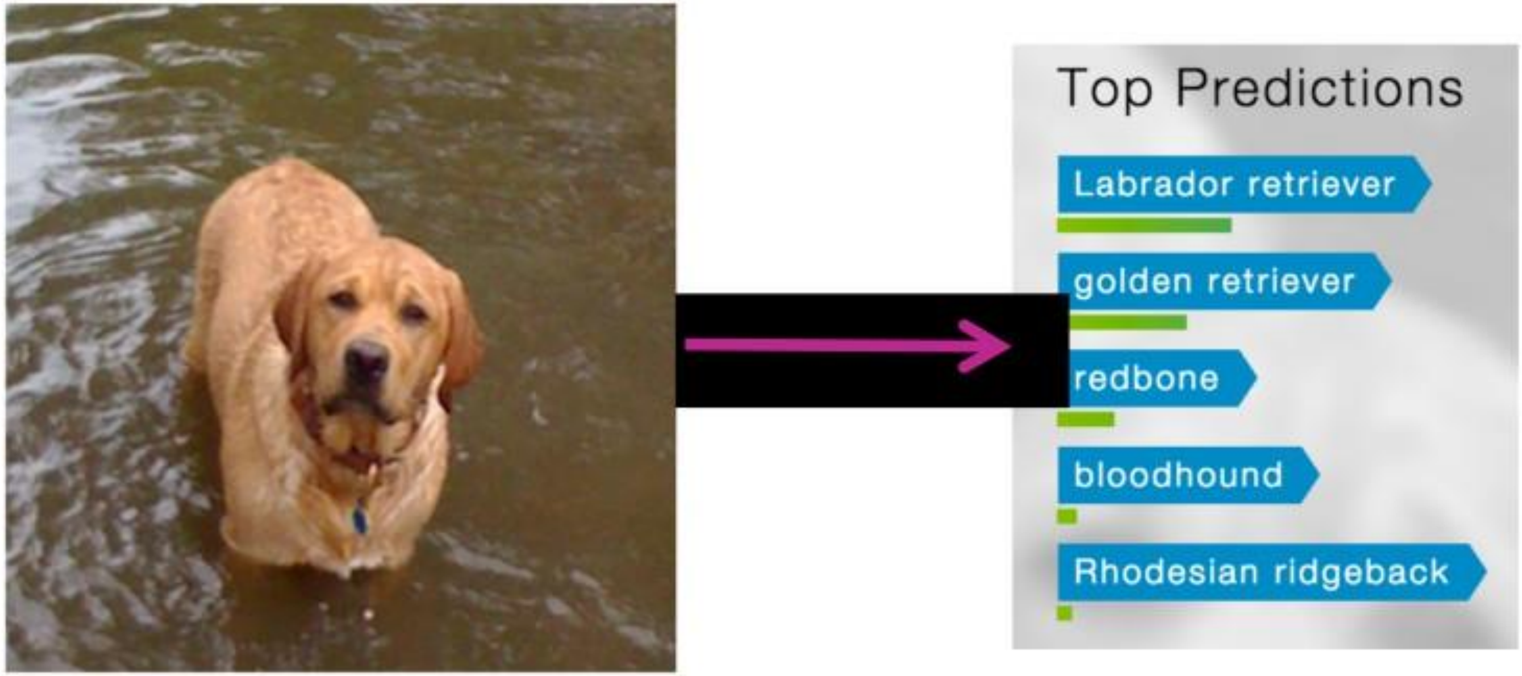
Spam

Input: x

Output: y

Text of email, sender, IP,…

Image classification



Input: x
Image pixels

Output: y
Predicted object

Personalized medical diagnosis

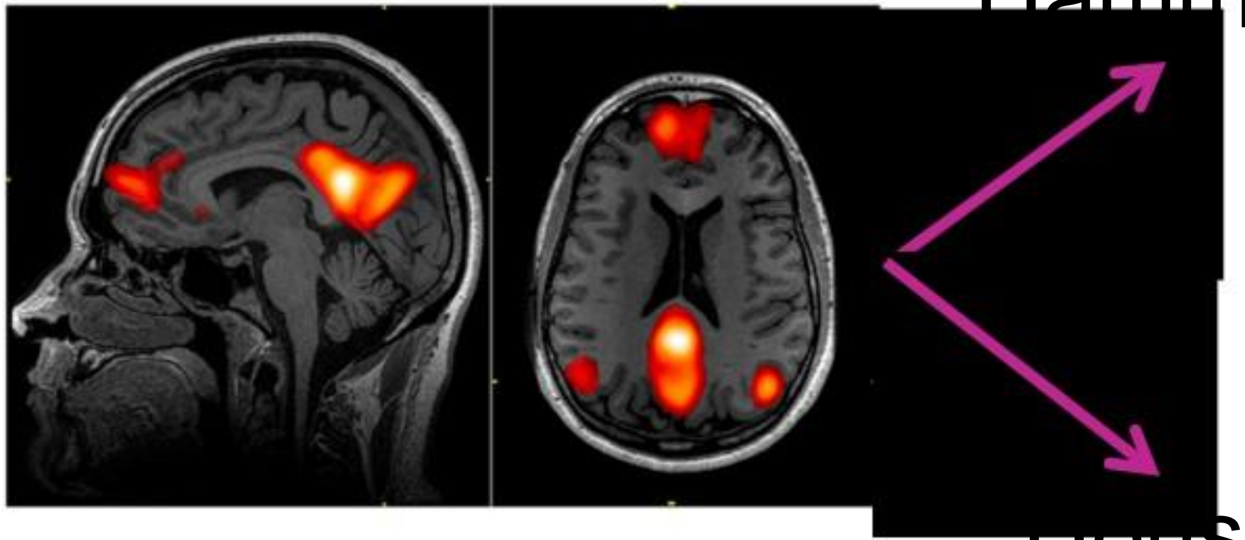
Input: x

Disease Classifier MODEL

Output: y

- Healthy
- Cold
- Flu
- Pneumonia
- …

Reading your mind



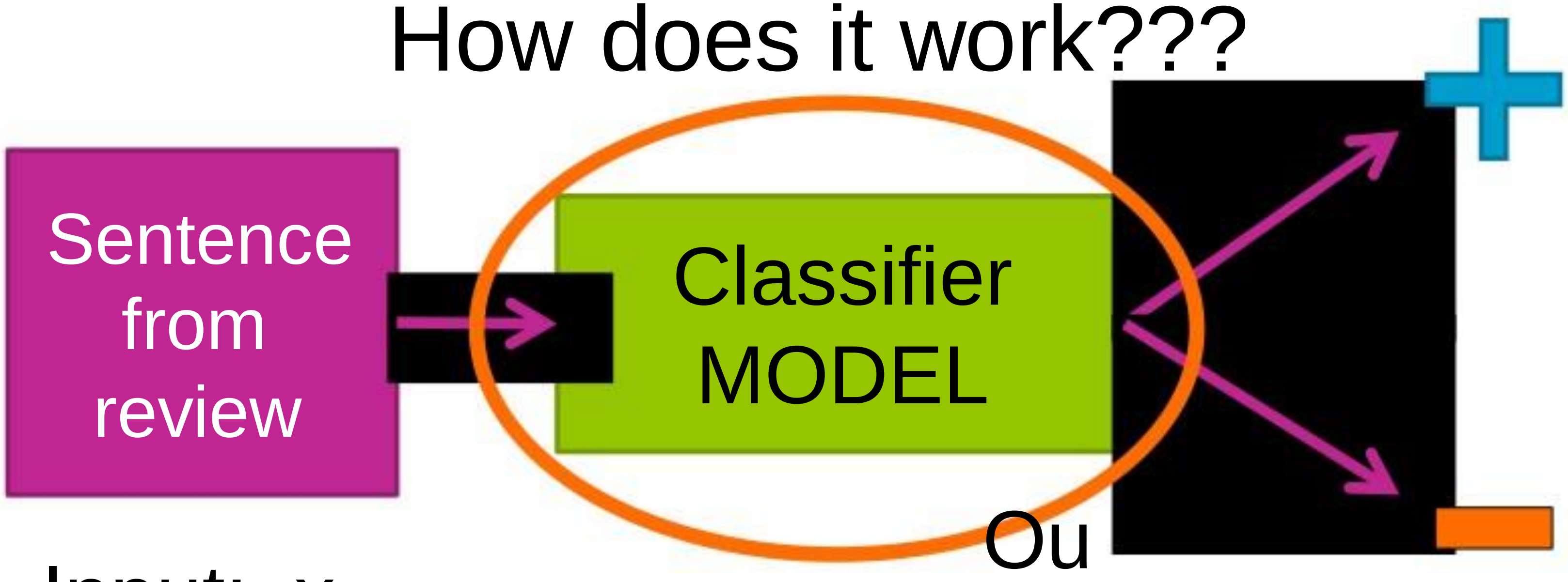
“Hammer”

“House”

Linear classifiers

Representing classifiers

How does it work???



Input: x

Predicted class

List of positive words	List of negative words
great, awesome, good, amazing,…	bad, terrible, disgusting, sucks,…

Simple thre[redacted]old classifier

Count positive & negative words in sentence

number of positive words >
number of negative words:
$\hat{y} = +$

Else:
$\hat{y} = -$

Sentence from review

Input: x

List of positive words	List of negative words
great, awesome, good, amazing,…	bad, terrible, disgusting, sucks,…

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

Simple thre[redacted]old classifier

Count positive & negative words in sentence

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

ŷ = +

Else:

ŷ = −

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* è Positive
  - *Not good* è 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	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.

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

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

if

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

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

Word	Weight
…	…

Simple line [redacted] lassifier

Score(x) = weighted count of words in sentence

Sentence from review

If *Score (x) > 0*:

$\hat{y}$ = +

Else:

$\hat{y}$ = −

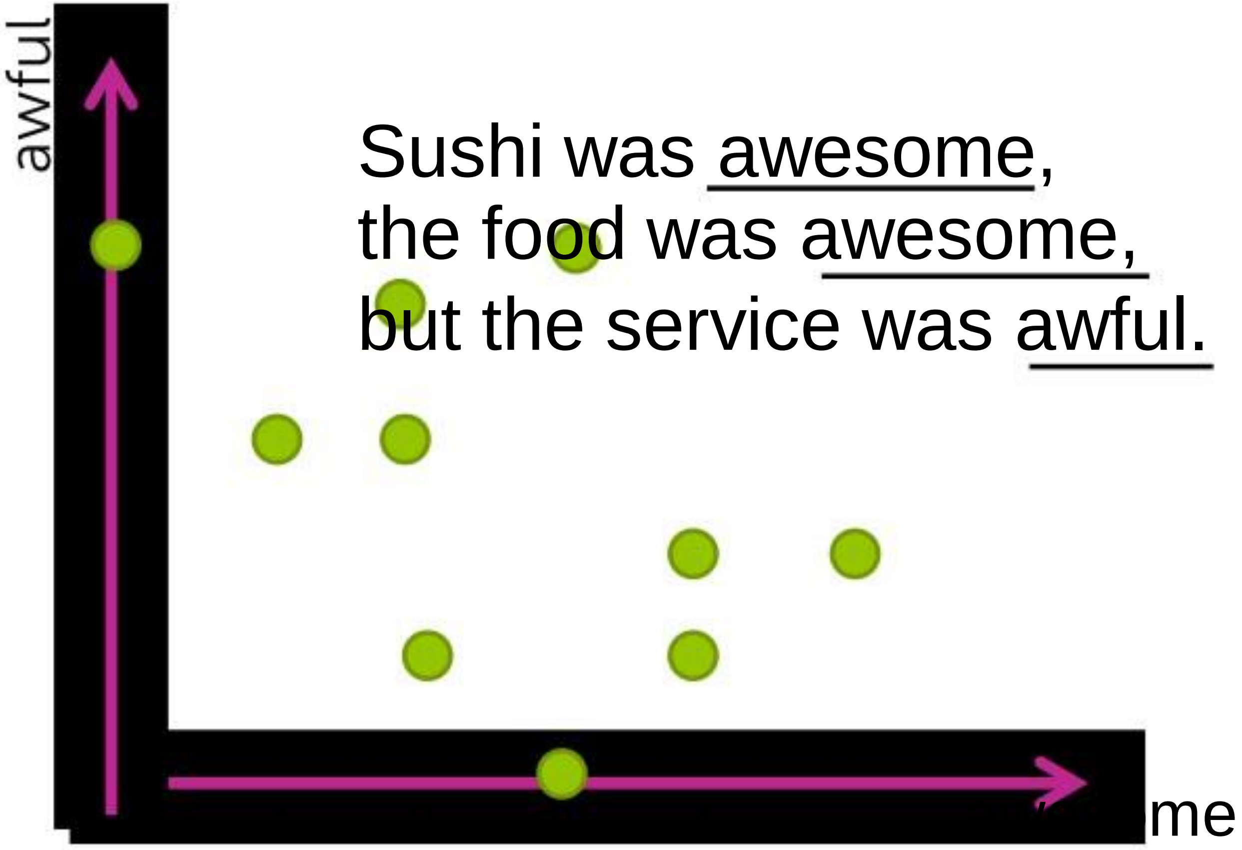
Input: x

Decision boundaries

Suppose only two words had non-zero weight

Word	Weight
awesome	1.0
awful	-1.5

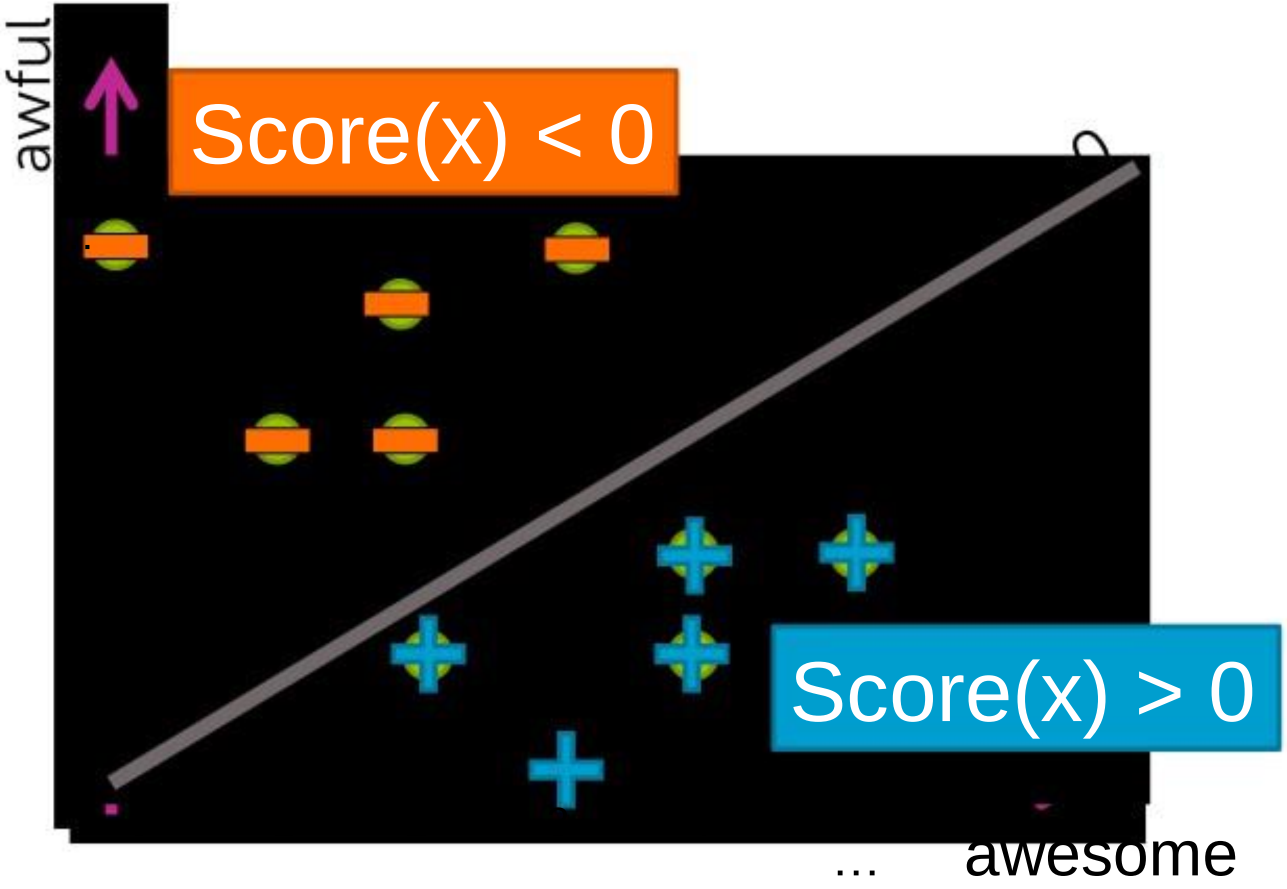
Score(x) = 1.0 #awesome - 1.5 #awful



Decision boundary example

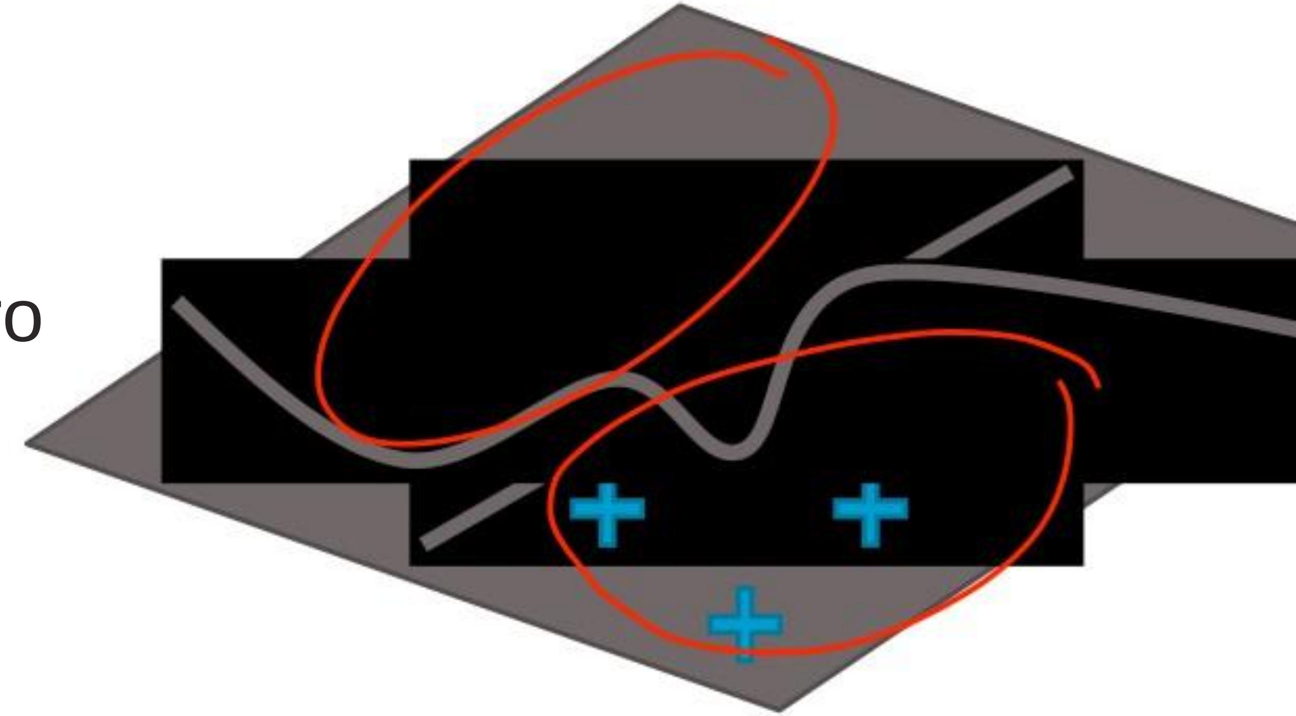
Word	Weight
awesome	1.0
awful	-1.5

Score(x) = 1.0 #awesome - 1.5 #awful



Decision boundary separates positive & negative predictions

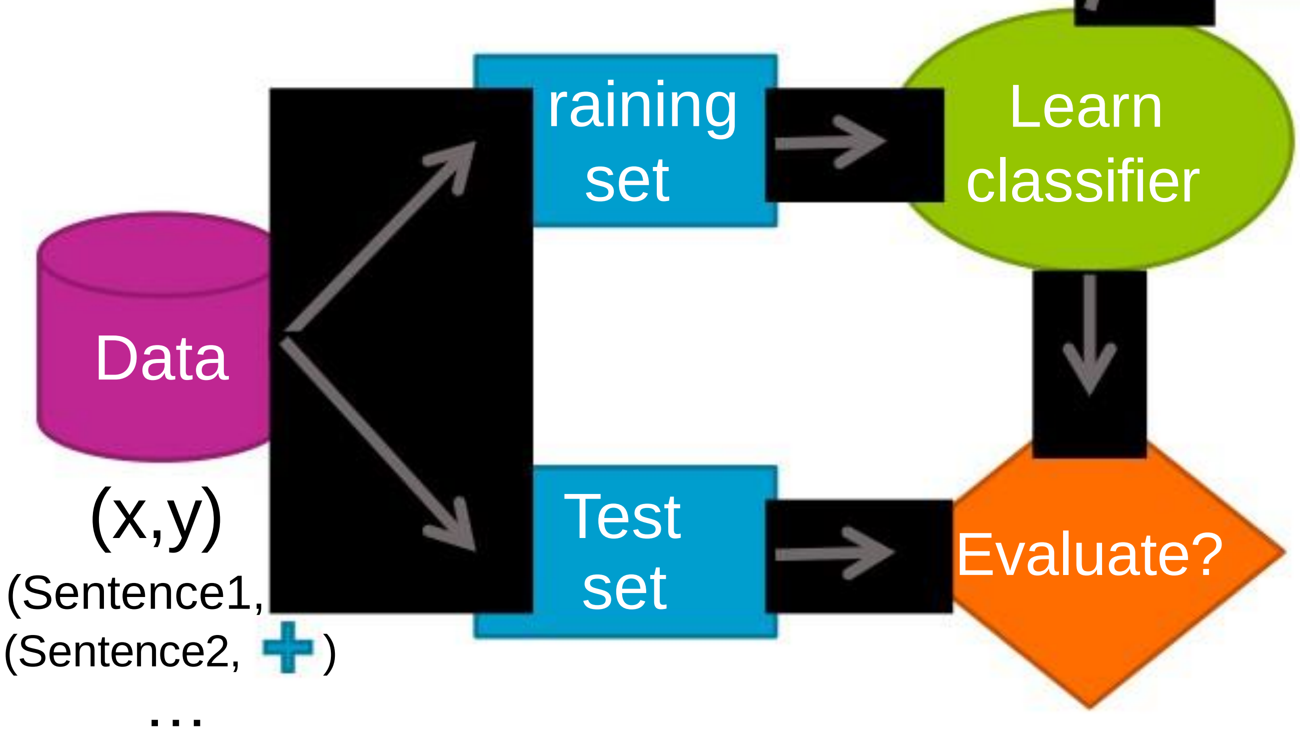
- For linear classifiers:
  - When 2 weights are non-zero
  è line
  - When 3 weights are non-zero
  è plane
  - When many weights are non-zero
  è hyperplane
- For more general classifiers
è more complicated shapes



Training and evaluating a classifier

Training a classifier = Learning the weights

Word	Weight
good	1.0
[redacted]esome	1.7
[redacted]d	-1.0
[redacted]ful	-3.3
	…



Classification error

Learned classifier

ŷ = +

Test example

((Food was OK, +))

Mistake!

Correct	1
Mistakes	1

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

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?

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

THANK YOU !!!!

ANY QUESTIONS ?????