CSE 258 – Lecture 3

Web Mining and Recommender Systems

Classification

Learning outcomes

This week we want to:

- Explore techniques for **classification**
- Try some simple solutions, and see why they might fail
- Explore more complex solutions, and their advantages and disadvantages
- Understand the relationship between classification and regression
- Examine how we can reliably **evaluate** classifiers under different conditions

CSE 258 – Lecture 3

Web Mining and Recommender Systems

Recap

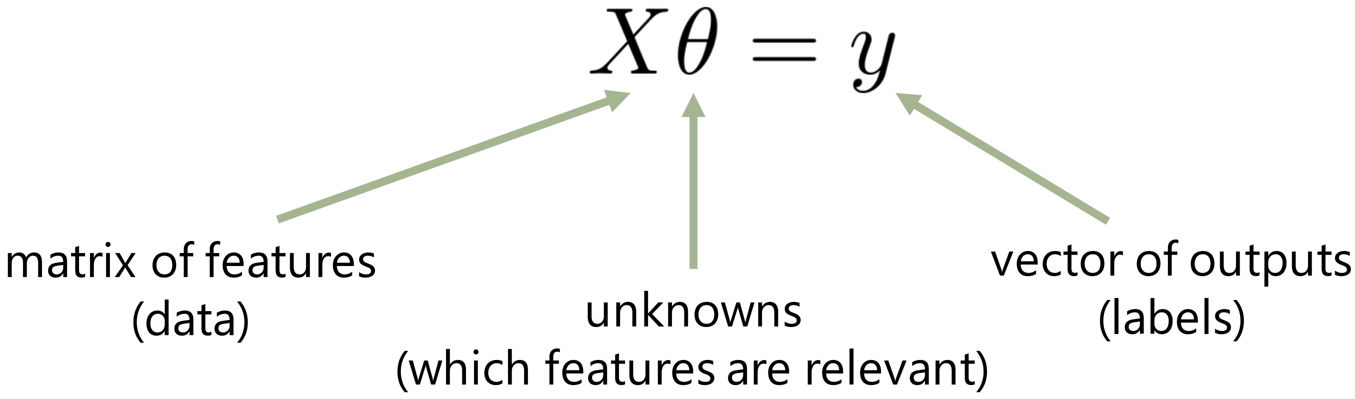
Last week…

Last week we started looking at **supervised learning problems**

$$f(\text{data}) \overset{?}{\rightarrow} \text{labels}$$

Last week...

We studied **linear regression**, in order to learn linear relationships between features and parameters to predict **real-valued** outputs



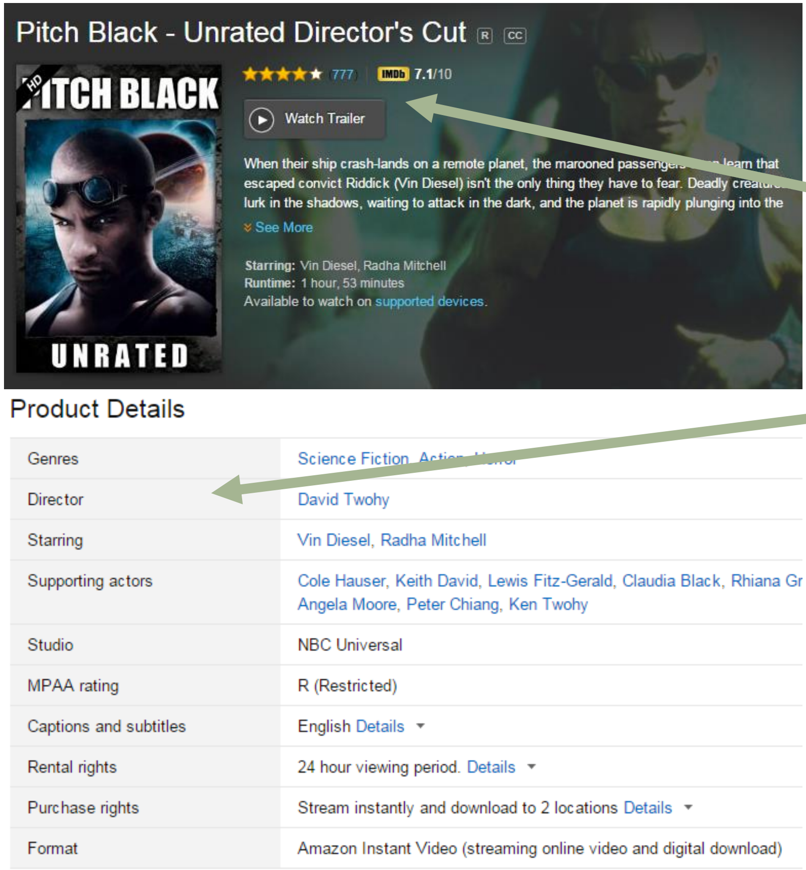
$$X\theta = y$$

matrix of features
(data)

unknowns
(which features are relevant)

vector of outputs
(labels)

Last week...



Pitch Black - Unrated Director's Cut R CC

★★★★★ 777 IMDb 7.1/10

Watch Trailer

When their ship crash-lands on a remote planet, the marooned passengers ... learn that escaped convict Riddick (Vin Diesel) isn't the only thing they have to fear. Deadly creatu... lurk in the shadows, waiting to attack in the dark, and the planet is rapidly plunging into the

See More

Starring: Vin Diesel, Radha Mitchell
Runtime: 1 hour, 53 minutes
Available to watch on supported devices.

Product Details

Genres	Science Fiction, Action, Horror
Director	David Twohy
Starring	Vin Diesel, Radha Mitchell
Supporting actors	Cole Hauser, Keith David, Lewis Fitz-Gerald, Claudia Black, Rhiana Gr Angela Moore, Peter Chiang, Ken Twohy
Studio	NBC Universal
MPAA rating	R (Restricted)
Captions and subtitles	English Details ▾
Rental rights	24 hour viewing period. Details ▾
Purchase rights	Stream instantly and download to 2 locations Details ▾
Format	Amazon Instant Video (streaming online video and digital download)

ratings

features

$$f(\text{user features}, \text{movie features}) \overset{?}{\to} \text{star rating}$$

Four important ideas from last week:

1) Regression can be cast in terms of **maximizing a likelihood**

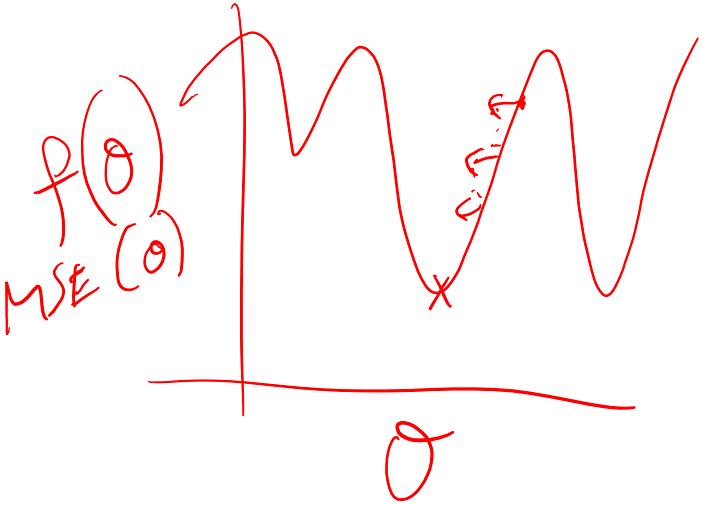
$$y_i = X_i \cdot \theta + \mathcal{N}(0, \sigma^2)$$

$$\max_\theta \prod_i p_\theta(y_i | X_i) = \min_\theta \sum_i (y_i - X_i \cdot \theta)^2$$

Four important ideas from last week:

2) Gradient descent for model optimization

```
1. Initialize $\theta$ at random
2. While (not converged) do
    $\theta := \theta - \alpha f'(\theta)$
```



Four important ideas from last week:

3) Regularization & Occam's razor

Regularization is the process of penalizing model complexity during training

$$\arg\min_\theta = \frac{1}{N}\|y - X\theta\|_2^2 + \lambda\|\theta\|_2^2$$

How much should we trade-off accuracy versus complexity?

Four important ideas from last week:

4) Regularization pipeline

1. Training set – select model parameters
2. Validation set – to choose amongst models (i.e., hyperparameters)
3. Test set – just for testing!

train | valid | test

train ↓ fit θ

valid ↓ choose λ

choosing among models

test ↓ generalization performance

Model selection

A **validation set** is constructed to "tune" the model's parameters

- Training set: used to **optimize the model's parameters**
- Test set: used to report how well we expect the model to perform on **unseen data**
- Validation set: used to **tune** any model parameters that are not directly optimized

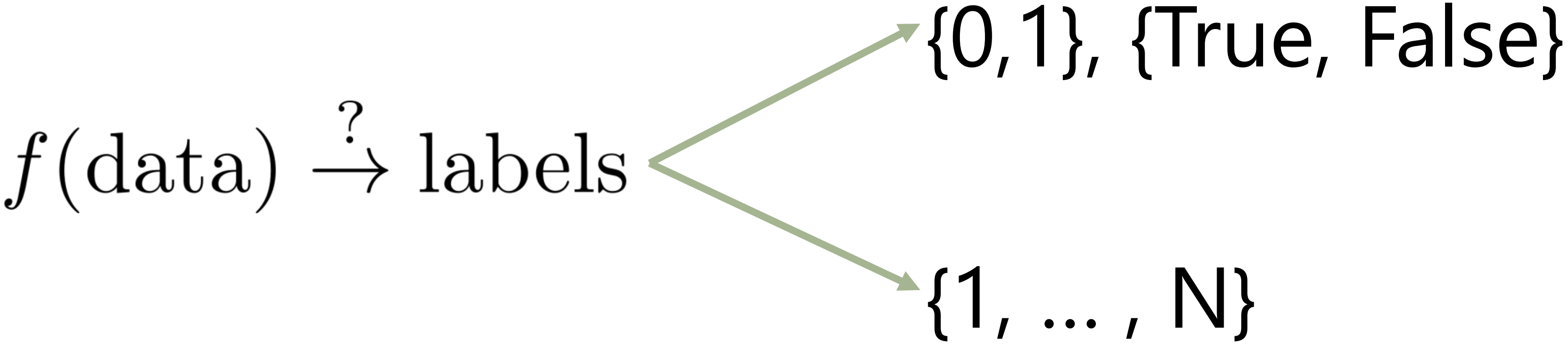
Model selection

A few “theorems” about training, validation, and test sets

- The training error **increases** as lambda **increases**
- The validation and test error are at least as large as the training error (assuming infinitely large random partitions)
- The validation/test error will usually have a “sweet spot” between under- and over-fitting

Today...

How can we predict **binary** or **categorical** variables?

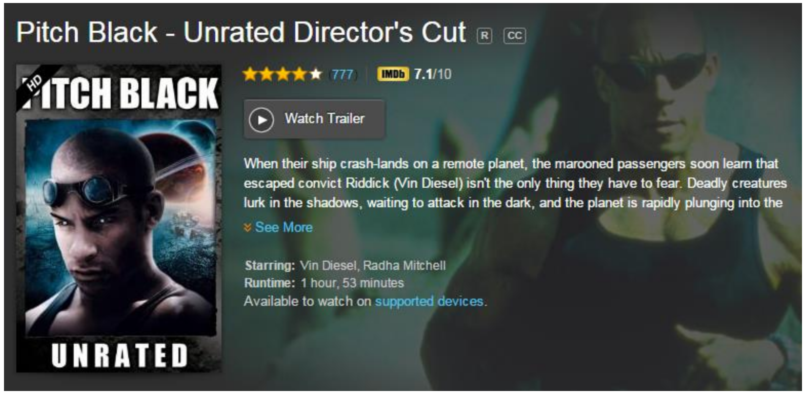


$f(\text{data}) \xrightarrow{?} \text{labels}$

{0,1}, {True, False}

{1, … , N}

Today…



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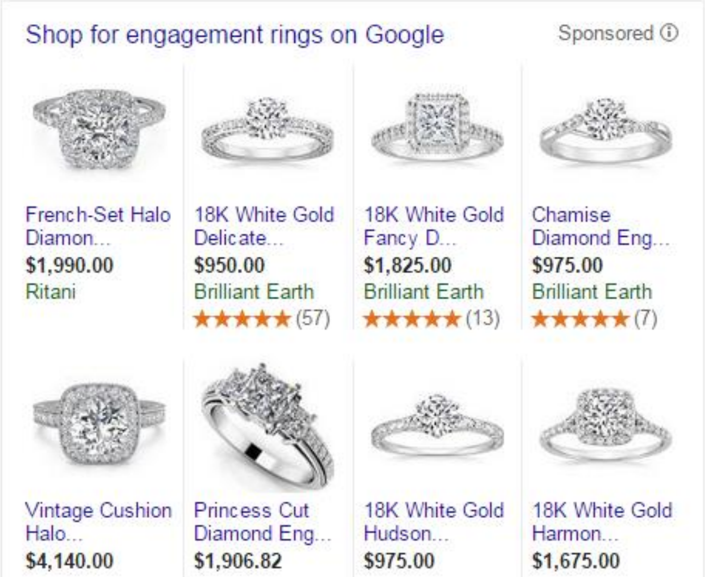
See More

Starring: Vin Diesel, Radha Mitchell
Runtime: 1 hour, 53 minutes
Available to watch on supported devices.

Will I **purchase** this product?

(yes)



Shop for engagement rings on Google

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French-Set Halo Diamon...
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Ritani

18K White Gold Delicate...
$950.00
Brilliant Earth
★★★★★ (57)

18K White Gold Fancy D...
$1,825.00
Brilliant Earth
★★★★★ (13)

Chamise Diamond Eng...
$975.00
Brilliant Earth
★★★★★ (7)

Vintage Cushion Halo...
$4,140.00

Princess Cut Diamond Eng...
$1,906.82

18K White Gold Hudson...
$975.00

18K White Gold Harmon...
$1,675.00

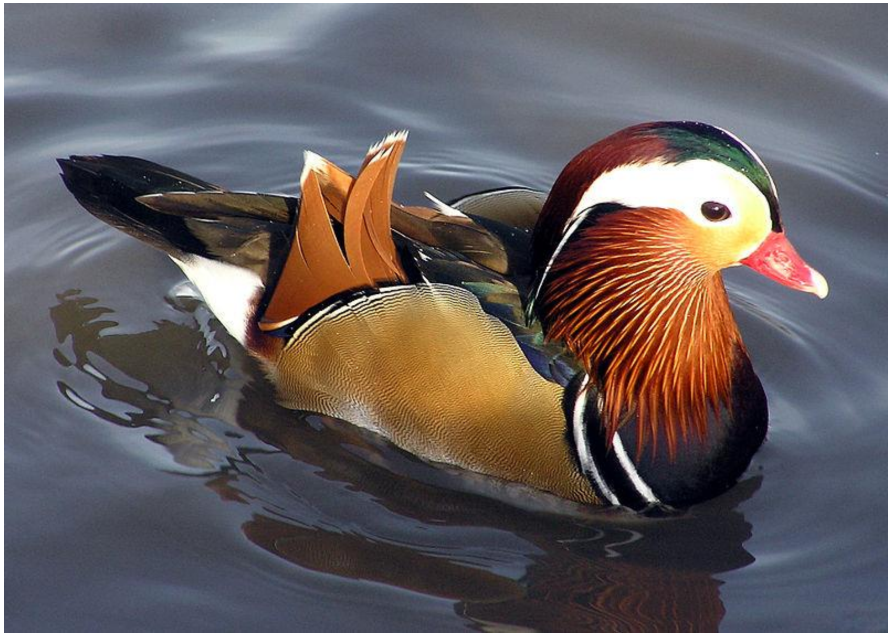
Will I **click on** this ad?

(no)

Today…

What animal appears in this image?

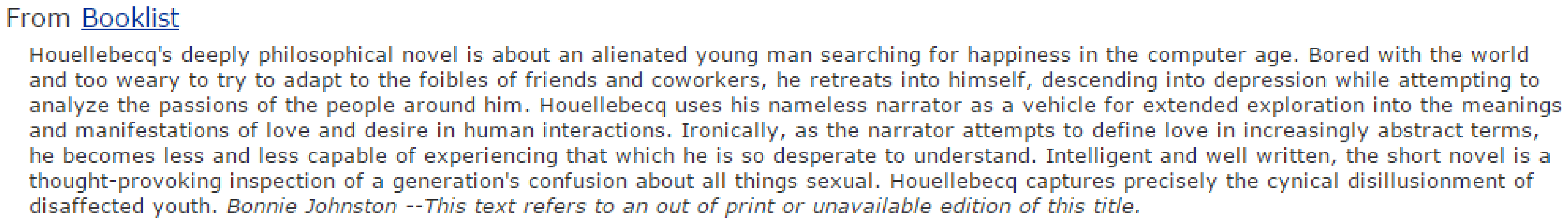
(mandarin duck)



Today…

What are the **categories** of the item being described?

(book, fiction, philosophical fiction)



From Booklist

Houellebecq's deeply philosophical novel is about an alienated young man searching for happiness in the computer age. Bored with the world and too weary to try to adapt to the foibles of friends and coworkers, he retreats into himself, descending into depression while attempting to analyze the passions of the people around him. Houellebecq uses his nameless narrator as a vehicle for extended exploration into the meanings and manifestations of love and desire in human interactions. Ironically, as the narrator attempts to define love in increasingly abstract terms, he becomes less and less capable of experiencing that which he is so desperate to understand. Intelligent and well written, the short novel is a thought-provoking inspection of a generation's confusion about all things sexual. Houellebecq captures precisely the cynical disillusionment of disaffected youth. *Bonnie Johnston --This text refers to an out of print or unavailable edition of this title.*

Today...

We'll attempt to build **classifiers** that make decisions according to rules of the form

$$y_i = \begin{cases} 1 & \text{if } X_i \cdot \theta > 0 \\ 0 & \text{otherwise} \end{cases}$$

This week…

1. Naïve Bayes

Assumes an **independence** relationship between the features and the class label and "learns" a simple model by counting

2. Logistic regression

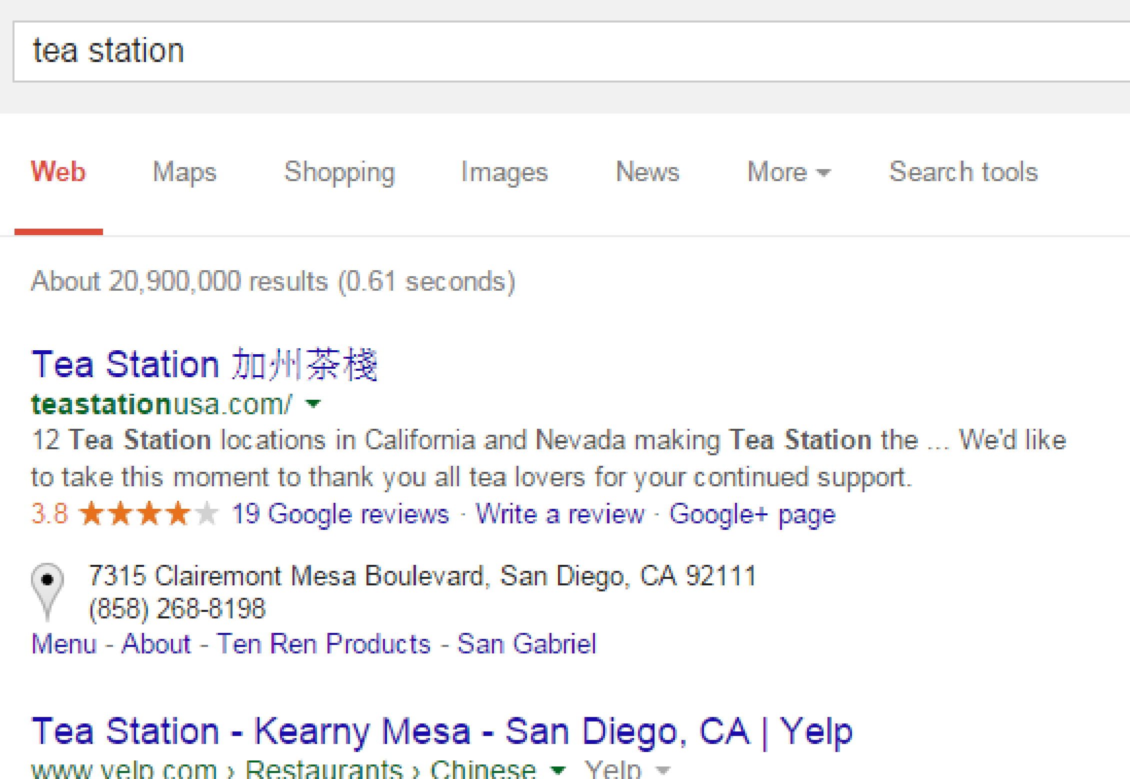
Adapts the **regression** approaches we saw last week to binary problems

3. Support Vector Machines

Learns to classify items by finding a hyperplane that separates them

This week...

Ranking results in order of how likely they are to be relevant



About 20,900,000 results (0.61 seconds)

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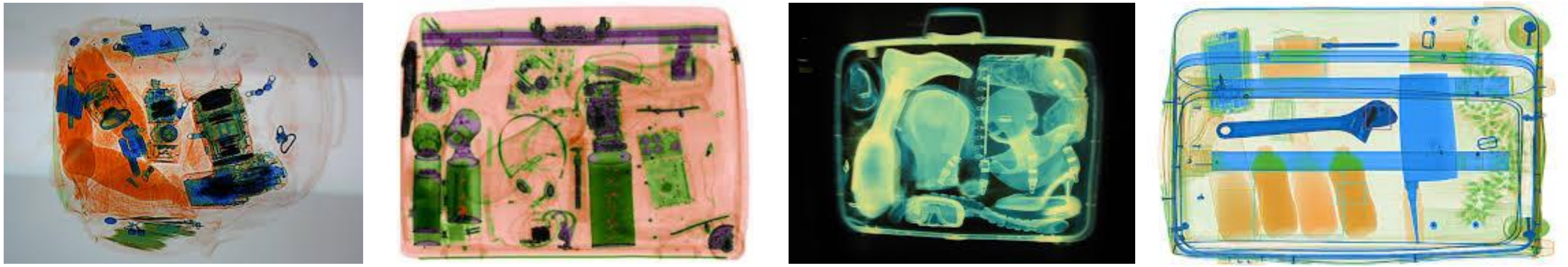
This week…

Evaluating classifiers

- False positives are nuisances but false negatives are disastrous (or vice versa)
- Some classes are very rare
- When we only care about the "most confident" predictions



e.g. which of these bags contains a weapon?

Naïve Bayes

We want to associate a probability with a label and its negation:

$$p(label|data)$$

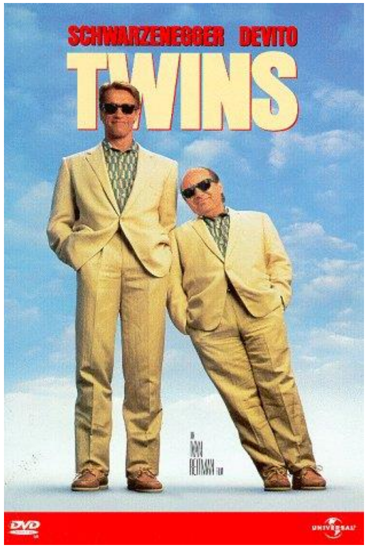
$$p(\neg label|data)$$

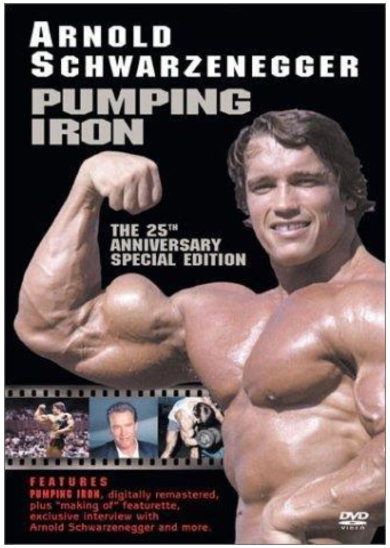
(classify according to whichever probability is greater than 0.5)

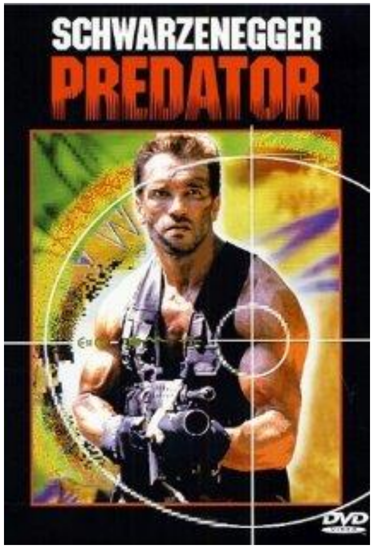
Q: How far can we get just by counting?

Naïve Bayes

e.g. p(movie is “action” | schwarzenneger in cast)




ARNOLD SCHWARZENEGGER
PUMPING IRON
THE 25TH ANNIVERSARY SPECIAL EDITION
FEATURES
PUMPING IRON, digitally remastered, plus "making of" featurette, exclusive interview with Arnold Schwarzenegger and more.
DVD



Just count!

#fims with Arnold = 45

#**action** films with Arnold = 32

p(movie is “action” | schwarzenneger in cast) = 32/45

$p(a)$

$p(a,b)$

$p(b|a) = \frac{p(a,b)}{p(a)}$

Naïve Bayes

What about:

p(movie is “action” |
schwarzenneger in cast **and**
release year = 2017 **and**
mpaa rating = PG **and**
budget < $1000000
)

#(training) fims with Arnold, released in 2017, rated PG, with a budged below $1M = 0

#(training) action fims with Arnold, released in 2017, rated PG, with a budged below $1M = 0

Naïve Bayes

Q: If we've never seen this combination of features before, what can we conclude about their probability?

A: We need some **simplifying assumption** in order to associate a probability with this feature combination

Naïve Bayes

Naïve Bayes assumes that features are **conditionally independent** given the label

$$(feature_i \perp\!\!\!\perp feature_j | label)$$

Naïve Bayes

$$(feature_i \perp\!\!\!\perp feature_j | label)$$

$$a \perp\!\!\!\perp b \Rightarrow p(a,b) = p(a)\,p(b)$$

$$a \perp\!\!\!\perp b | c \Rightarrow p(a,b|c) = p(a|c)\,p(b|c)$$

a = I'm wearing shorts

b = you're wearing shorts

c = it's summer

Conditional independence?

$$(a \perp\!\!\!\perp b | c)$$

(a is conditionally independent of b, given c)

"if you know **c**, then knowing **a** provides no additional information about **b**"

$$(\text{I remembered my umbrella} \perp\!\!\!\perp \text{the streets are wet} \mid \text{it's raining})$$

Naïve Bayes

$$(feature_i \perp\!\!\!\perp feature_j | label)$$

$$\downarrow$$

$$p(feature_i, feature_j | label)$$

$$=$$

$$p(feature_i | label) p(feature_j | label)$$

Naïve Bayes

posterior

prior

likelihood

$$p(label|features) = \frac{p(label)\, p(features \mid label)}{p(features)}$$

evidence

$$p(a|b) = \frac{p(a)p(b|a)}{p(b)}$$

$$\underset{\text{C.I.}}{=} \frac{p(label) \prod_i p(feature_i \mid label)}{p(features)}$$

Naïve Bayes

$$p(label|features) = \frac{p(label)\prod_i p(feature_i|label)}{\underbrace{p(features)}}$$

$$p(\neg label|features) = p(\neg label)\frac{\prod_i p(\overset{?}{feat}_i|label)}{p(features)}$$

The denominator doesn’t matter, because we really just care about

$$p(label|features) \quad \text{vs.} \quad p(\neg label|features)$$

both of which have the same denominator

Naïve Bayes

$$\frac{p(y)\prod_i p(f_i|y)}{p(\neg y)\prod_i p(f_i|\neg y)} \underset{?}{>} 1$$

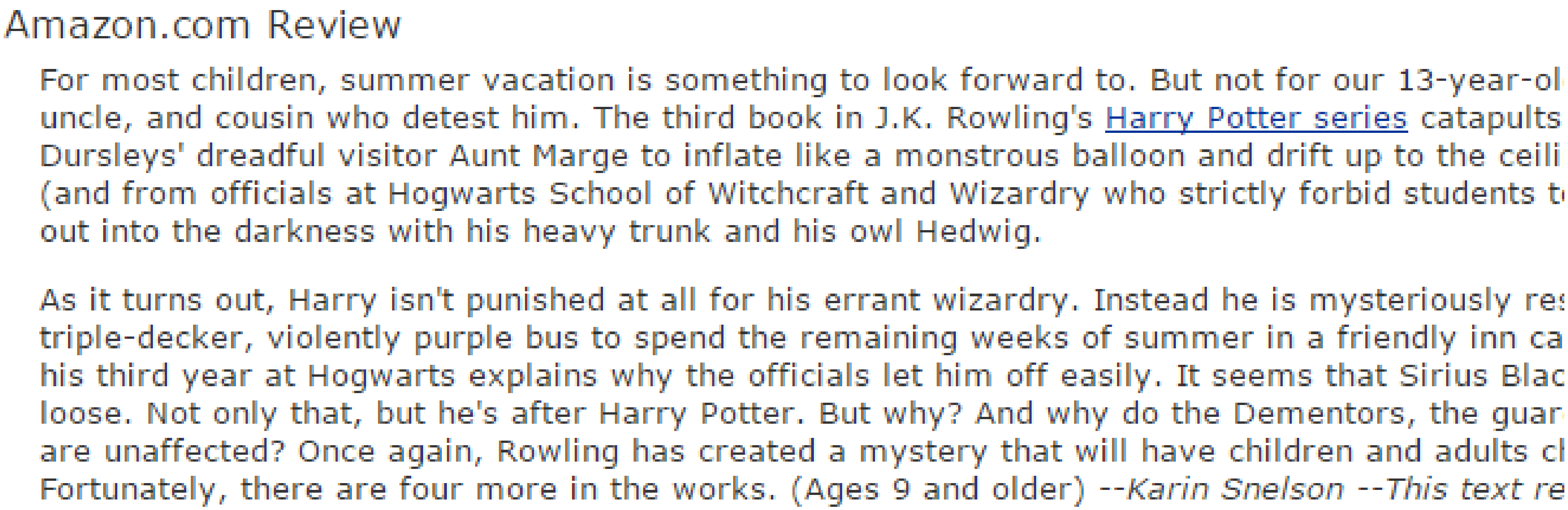
The denominator doesn’t matter, because we really just care about

$$p(label|features) \quad \text{vs.} \quad p(\neg label|features)$$

both of which have the same denominator

Example 1

Amazon editorial descriptions:



Amazon.com Review

For most children, summer vacation is something to look forward to. But not for our 13-year-ol
uncle, and cousin who detest him. The third book in J.K. Rowling's Harry Potter series catapults
Dursleys' dreadful visitor Aunt Marge to inflate like a monstrous balloon and drift up to the ceili
(and from officials at Hogwarts School of Witchcraft and Wizardry who strictly forbid students t
out into the darkness with his heavy trunk and his owl Hedwig.

As it turns out, Harry isn't punished at all for his errant wizardry. Instead he is mysteriously res
triple-decker, violently purple bus to spend the remaining weeks of summer in a friendly inn ca
his third year at Hogwarts explains why the officials let him off easily. It seems that Sirius Blac
loose. Not only that, but he's after Harry Potter. But why? And why do the Dementors, the guar
are unaffected? Once again, Rowling has created a mystery that will have children and adults cl
Fortunately, there are four more in the works. (Ages 9 and older) --*Karin Snelson* --*This text re*

50k descriptions:

http://jmcauley.ucsd.edu/cse258/data/amazon/book_descriptions_50000.json

Example 1

P(book is a children's book |
"wizard" is mentioned in the description **and**
"witch" is mentioned in the description)

Code available on:

http://jmcauley.ucsd.edu/cse258/code/week2.py

Example 1

Conditional independence assumption:

“if you know **a book is for children**, then knowing that **wizards are mentioned** provides no additional information about whether **witches are mentioned**”

obviously ridiculous

Double-counting

Q: What would happen if we trained two regressors, and attempted to “naively” combine their parameters?

Double-counting

height = 1.2 weight

height = 15 shoe size

$$H = 1.2w + 15 s.s.$$

Double-counting

A: Since both features encode essentially the same information, we'll end up **double-counting** their effect

Logistic regression

Logistic Regression also aims to model

$$p(label|data)$$

By training a classifier of the form

$$y_i = \begin{cases} 1 & \text{if } X_i \cdot \theta > 0 \\ 0 & \text{otherwise} \end{cases}$$

Logistic regression

Last week: regression

$$y_i = X_i \cdot \theta$$

This week: logistic regression

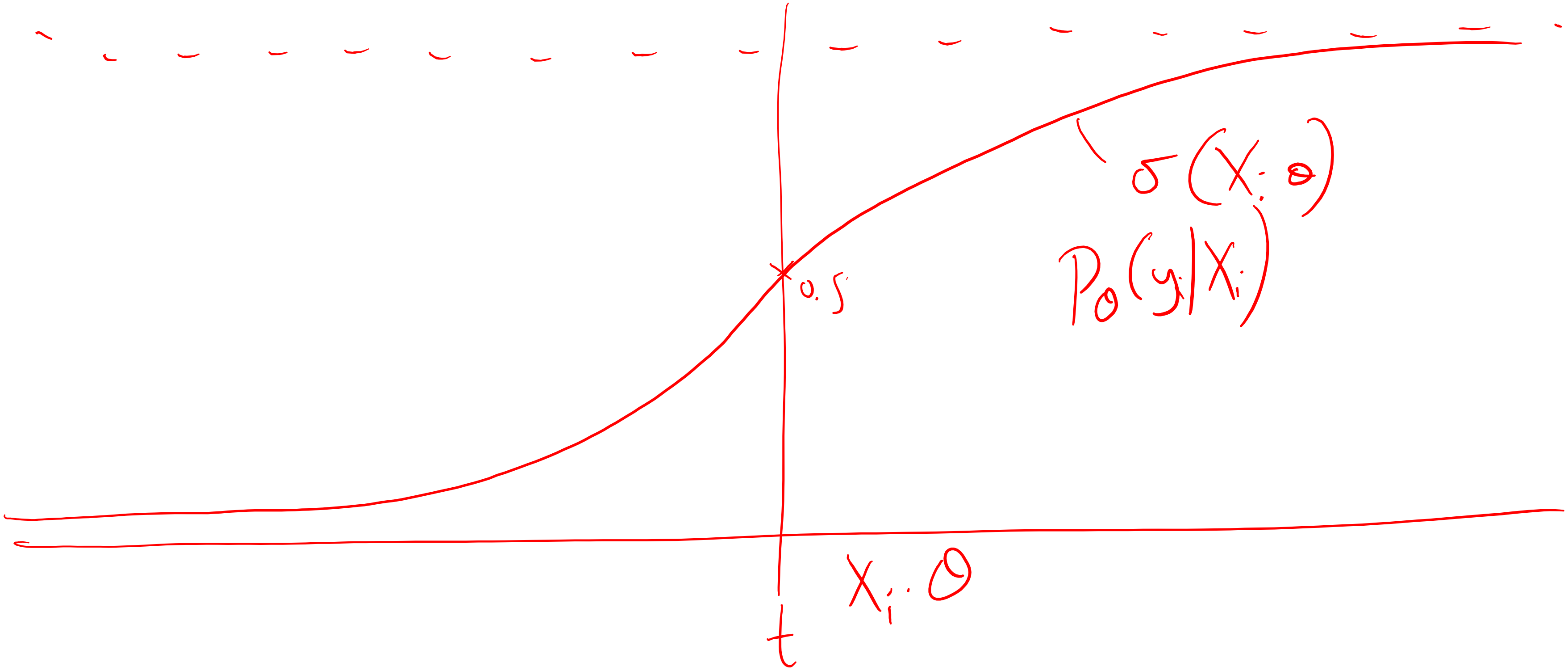
$$y_i = \begin{cases} 1 & \text{if } X_i \cdot \theta > 0 \\ 0 & \text{otherwise} \end{cases}$$

Logistic regression

Q: How to convert a real-valued expression ($X_i \cdot \theta \in \mathbb{R}$) Into a probability ($p_\theta(y_i | X_i) \in [0, 1]$)

Logistic regression

A: sigmoid function: $\sigma(t) = \frac{1}{1+e^{-t}}$



Logistic regression

Training:

$X_i \cdot \theta$ should be maximized when y_i is positive and minimized when y_i is negative

$$\arg\max_\theta \prod_{y_i=1} p_\theta(y_i|X_i) \times \prod_{y_i=0} \left(1 - p_\theta(y_i|X_i)\right)$$

$$\prod_{y_i=1} \sigma(X_i \cdot \theta) \times \prod_{y_i=0} \left(1 - \sigma(X_i \cdot \theta)\right)$$

Logistic regression

How to optimize?

$$L_\theta(y|X) = \prod_{y_i=1} p_\theta(y_i|X_i) \prod_{y_i=0}(1 - p_\theta(y_i|X_i))$$

- Take logarithm
- **Subtract** regularizer
- Compute gradient
- Solve using gradient **ascent**

Logistic regression

$$L_\theta(y|X) = \prod\nolimits_{y_i=1} p_\theta(y_i|X_i) \prod\nolimits_{y_i=0}(1 - p_\theta(y_i|X_i))$$

$$\ell_\theta(y|X) = \sum_{y_i=1} \log \sigma(X_i \cdot \theta) + \sum_{y_i=0} \log(1-\sigma(X_i \cdot \theta))$$

$$= \sum_{y_i=1} \log\left(\frac{1}{1+e^{-X_i \cdot \theta}}\right) + \sum_{y_i=0} \log\left(\frac{e^{-X_i \cdot \theta}}{1+e^{-X_i \cdot \theta}}\right)$$

$$= \sum_{y} -\log(1+e^{-X_i \cdot \theta}) + \sum_{y_i=0} -X_i \cdot \theta$$

Logistic regression

$$l_\theta(y|X) = \sum_i -\log(1 + e^{-\underbrace{X_i \cdot \theta}_{\sum_k x_{ik}\theta_k}}) + \sum_{y_i=0} -X_i \cdot \theta - \lambda\|\theta\|_2^2$$

$$\frac{\partial l}{\partial \theta_k} = \sum_i \frac{x_{ik} e^{-X_i \cdot \theta}}{1 + e^{-X_i \cdot \theta}} + \sum_{y_i=0} -x_{ik} - 2\lambda\theta_k$$

$$= \sum_i x_{ik}\left(1 - \sigma(X_i \cdot \theta)\right) + \sum_{y_i=0} -x_{ik} - 2\lambda\theta_k$$

Logistic regression

Log-likelihood:

$$l_\theta(y|X) = \sum_i -\log(1 + e^{-X_i \cdot \theta}) + \sum_{y_i=0} -X_i \cdot \theta - \lambda \|\theta\|_2^2$$

Derivative:

$$\frac{\partial l}{\partial \theta_k} = \sum_i X_{ik}(1 - \sigma(X_i \cdot \theta)) + \sum_{y_i=0} -X_{ik} - 2\lambda\theta_k$$

Multiclass classification

The most ~~common~~ Simple way to generalize **binary** classification (output in {0,1}) to **multiclass** classification (output in {1 … N}) is simply to train a binary predictor for each class

e.g. based on the description of this book:

- Is it a Children’s book? {yes, no}
- Is it a Romance? {yes, no}
- Is it Science Fiction? {yes, no}
- …

In the event that predictions are inconsistent, choose the one with the highest confidence

Questions?

Further reading:

- On Discriminative vs. Generative classifiers: A comparison of logistic regression and naïve Bayes (Ng & Jordan '01)
- Boyd-Fletcher-Goldfarb-Shanno algorithm (BFGS)

CSE 258 – Lecture 3

Web Mining and Recommender Systems

Supervised Learning - Support Vector Machines

So far we've seen...

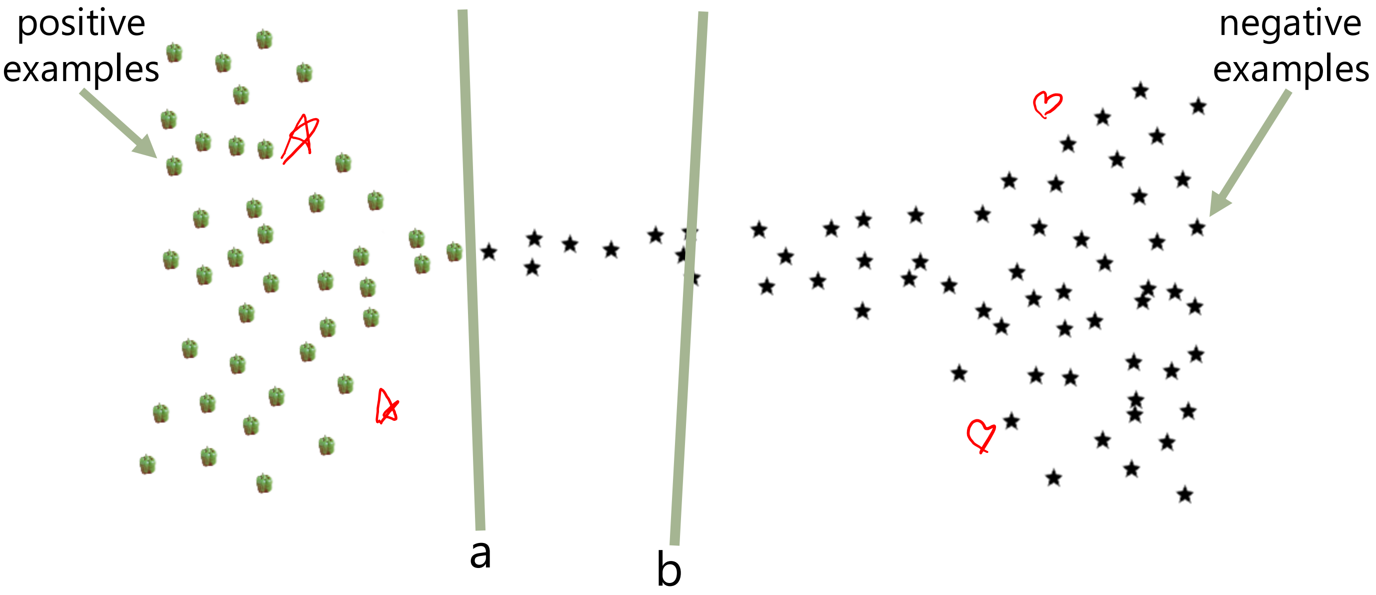
So far we've looked at **logistic regression,** which is a classification model of the form:

$$y_i = \begin{cases} 1 & \text{if } X_i \cdot \theta > 0 \\ 0 & \text{otherwise} \end{cases}$$

- In order to do so, we made certain **modeling assumptions,** but there are many different models that rely on different assumptions
- In this lecture we'll look at another such model

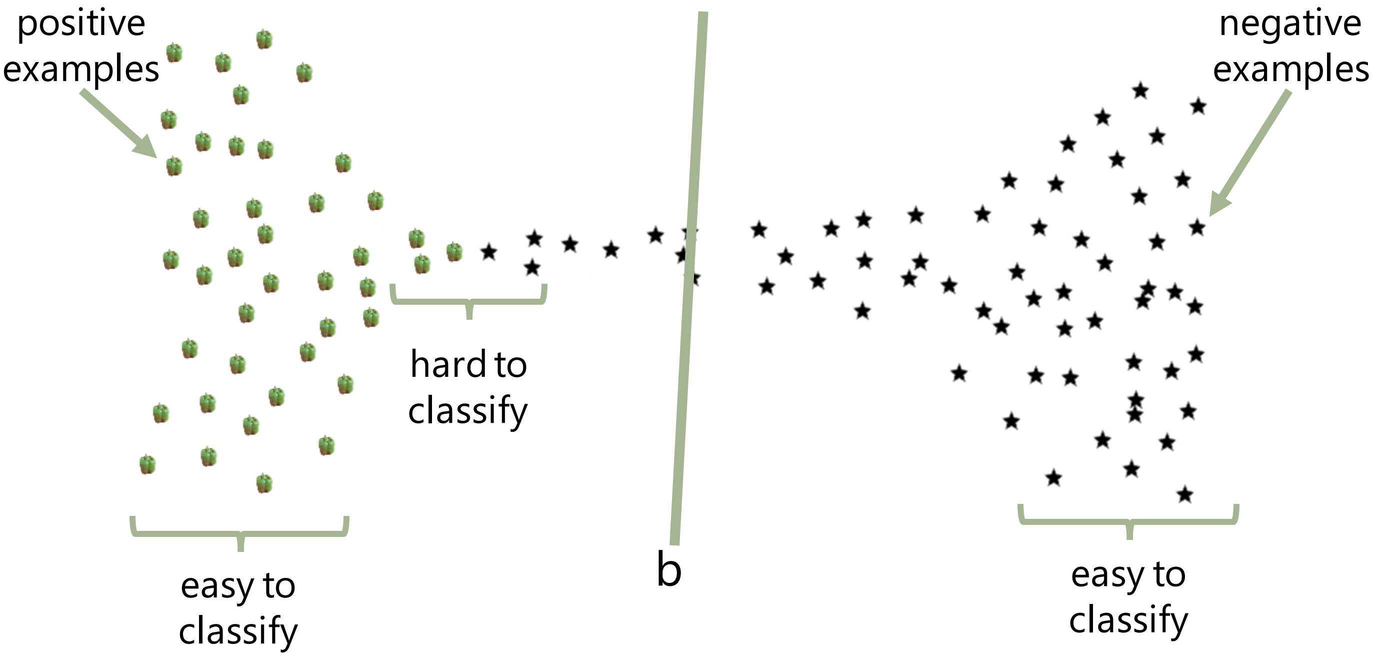
Motivation: SVMs vs Logistic regression

Q: Where would a logistic regressor place the decision boundary for these features?



SVMs vs Logistic regression

Q: Where would a logistic regressor place the decision boundary for these features?

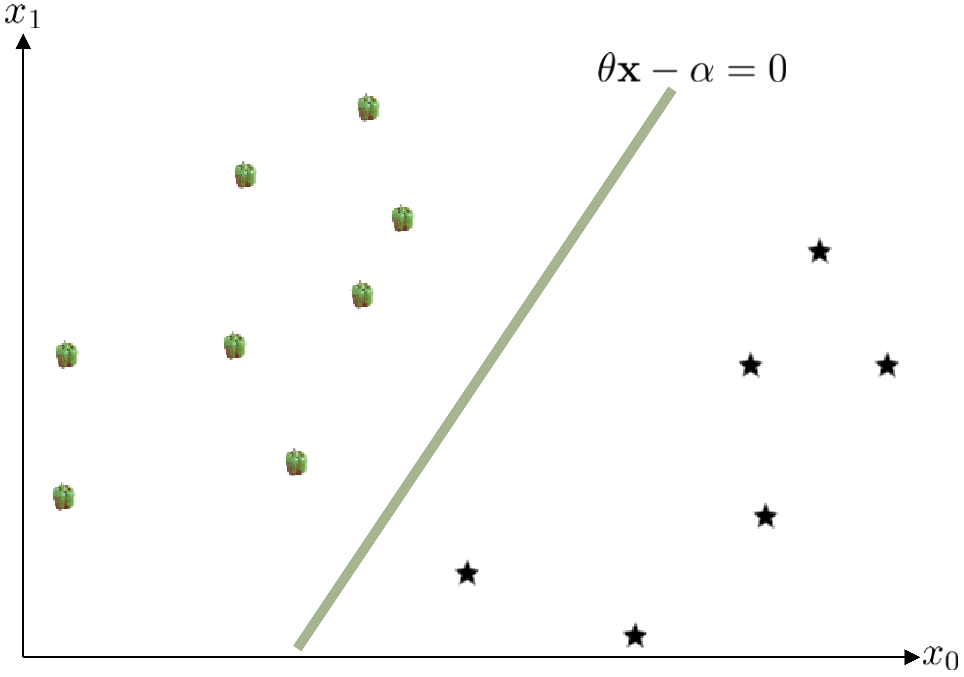


SVMs vs Logistic regression

- Logistic regressors don't optimize the number of "mistakes"
- No special attention is paid to the "difficult" instances – every instance influences the model
- But "easy" instances can affect the model (and in a bad way!)
- How can we develop a classifier that optimizes the number of mislabeled examples?

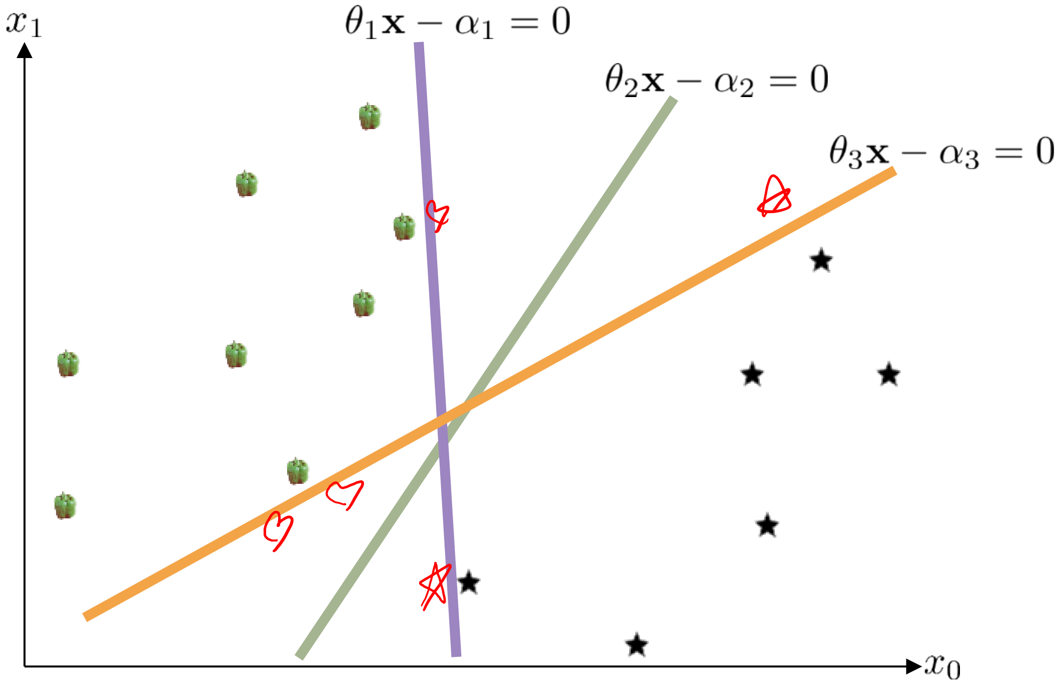
Support Vector Machines: Basic idea

A classifier can be defined by the hyperplane (line) $\theta\mathbf{x} - \alpha = 0$



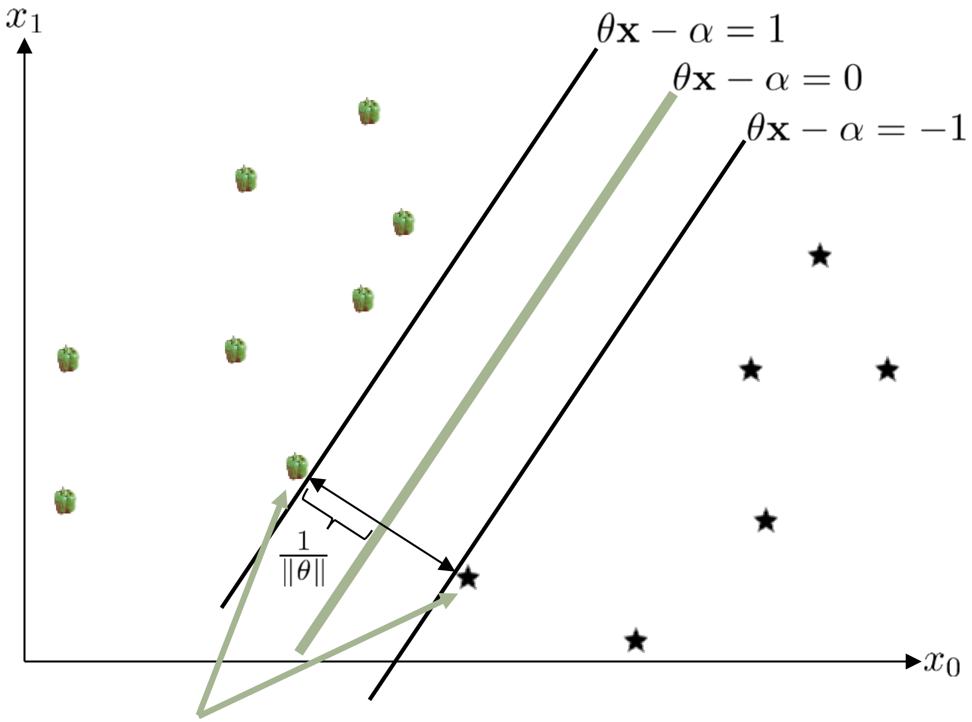
Support Vector Machines: Basic idea

Observation: Not all classifiers are equally good



x_1
$\theta_1 \mathbf{x} - \alpha_1 = 0$
$\theta_2 \mathbf{x} - \alpha_2 = 0$
$\theta_3 \mathbf{x} - \alpha_3 = 0$
x_0

Support Vector Machines


x_1
$\theta \mathbf{x} - \alpha = 1$
$\theta \mathbf{x} - \alpha = 0$
$\theta \mathbf{x} - \alpha = -1$
$\frac{1}{\|\theta\|}$
x_0

“support vectors”

- An SVM seeks the classifier (in this case a line) that is **furthest from the nearest points**
- This can be written in terms of a specific optimization problem:

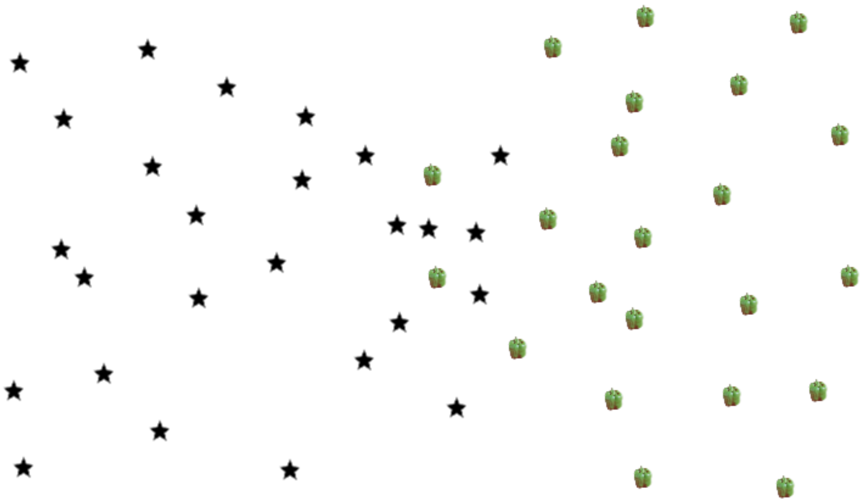
$$\arg\min_{\theta,\alpha} \frac{1}{2}\|\theta\|_2^2$$

such that

$$\forall_i y_i(\theta \cdot X_i - \alpha) \geq 1$$

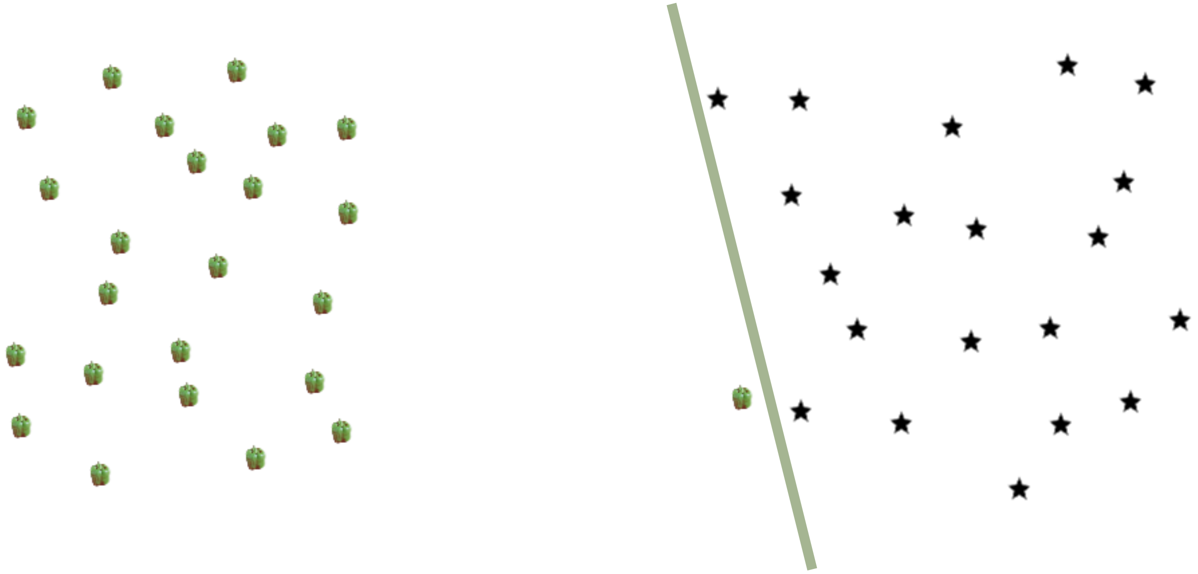
Support Vector Machines

But: is finding such a separating hyperplane even possible?



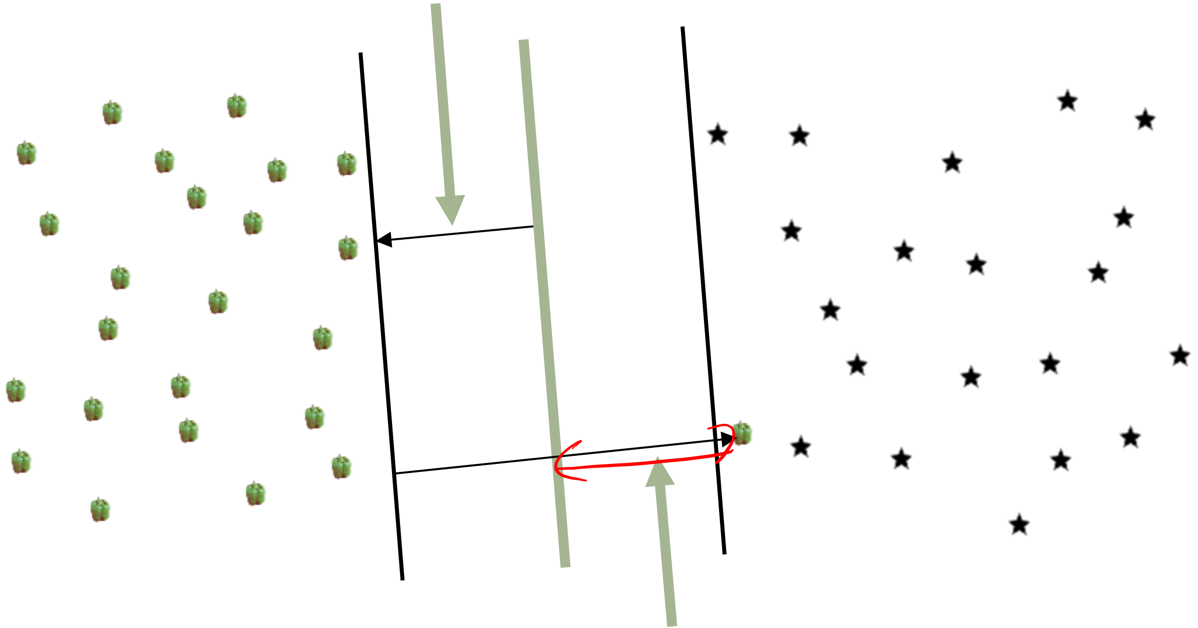
Support Vector Machines

Or: is it actually a good idea?



Support Vector Machines

Want the margin to be as wide as possible



While penalizing points on the wrong side of it

Support Vector Machines

Soft-margin formulation:

$$\arg\min_{\theta,\alpha,\xi>0} \tfrac{1}{2}\|\theta\|_2^2 + C\textstyle\sum_i \xi_i$$

such that

$$\forall_i y_i(\theta \cdot X_i - \alpha) \geq 1 - \xi_i$$

Summary of Support Vector Machines

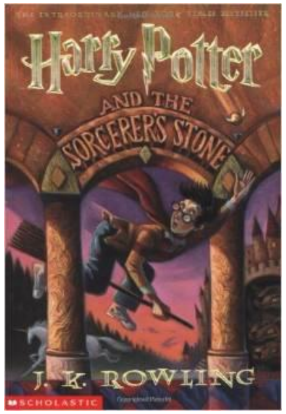
- SVMs seek to find a hyperplane (in two dimensions, a line) that optimally separates two classes of points
- The “best” classifier is the one that classifies all points correctly, such that the nearest points are **as far as possible** from the boundary
- If not all points can be correctly classified, a penalty is incurred that is proportional to **how badly the points are misclassified** (i.e., their distance from this hyperplane)

CSE 258 – Lecture 3

Web Mining and Recommender Systems

Supervised Learning - Code example

Judging a book by its cover



$$\underbrace{[0.723845, 0.153926, 0.757238, 0.983643, \ldots]}_{\text{4096-dimensional image features}}$$

Images features are available for each book on
http://jmcauley.ucsd.edu/cse258/data/amazon/book_images_5000.json

http://caffe.berkeleyvision.org/

Judging a book by its cover

Example: train a classifier to predict whether a book is a children's book from its cover art

(code available on)
http://jmcauley.ucsd.edu/code/week2.py

Judging a book by its cover

- The number of errors we made was extremely low, yet our classifier doesn’t seem to be very good – why?

(stay tuned next lecture!)

Summary

The classifiers we've seen today all attempt to make decisions by associating weights (theta) with features (x) and classifying according to

$$y_i = \begin{cases} 1 & \text{if } X_i \cdot \theta > 0 \\ 0 & \text{otherwise} \end{cases}$$

Summary

- **Naïve Bayes**
  - Probabilistic model (fits $p(label|data)$)
  - Makes a conditional independence assumption of the form $(feature_i \perp\!\!\!\perp feature_j|label)$ allowing us to define the model by computing $p(feature_i|label)$ for each feature
  - Simple to compute just by counting
- **Logistic Regression**
  - Fixes the "double counting" problem present in naïve Bayes
- **SVMs**
  - Non-probabilistic: optimizes the classification error rather than the likelihood

Questions?