University of Southampton

COMP6237 Data Mining
Lecture 6: Document Filtering

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Lecture slides available here:

http://comp6237.ecs.soton.ac.uk/zh.html

(Thanks to Prof. Jonathon Hare and Dr. Jo Grundy for providing the lecture materials used to develop the slides.)

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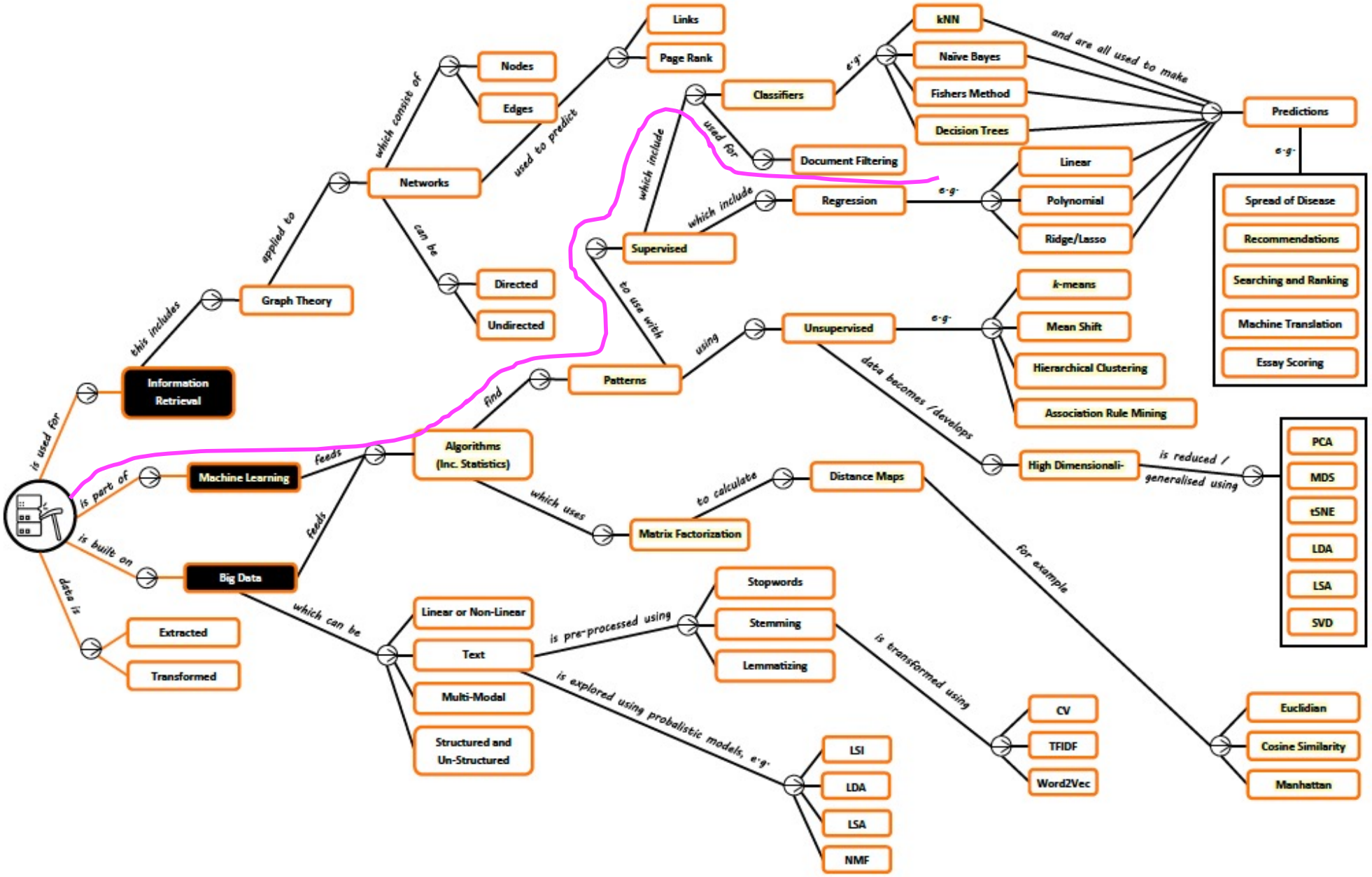
Document Filtering – **Roadmap**



Document Filtering – **Textbook**

University of Southampton

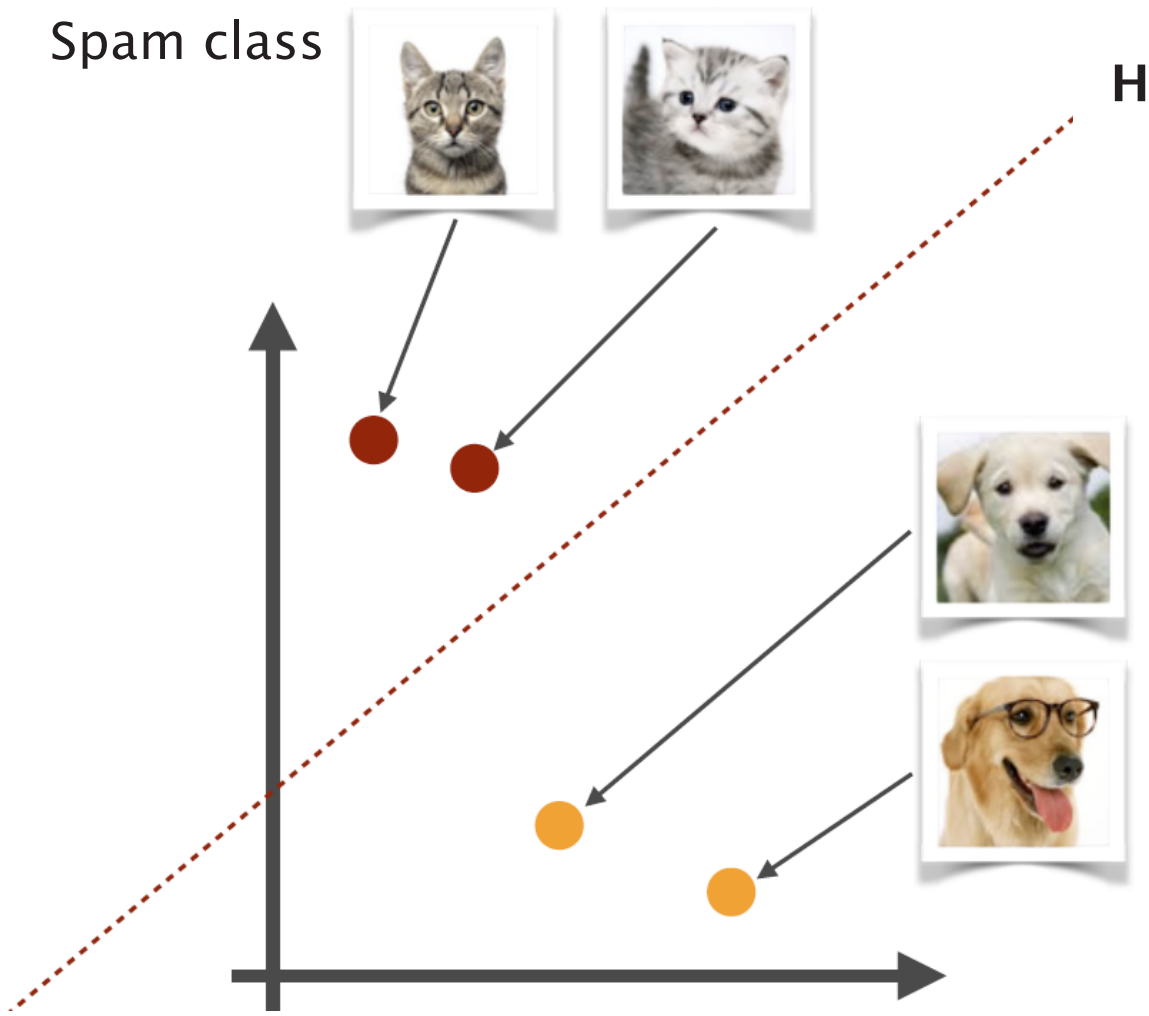
CHAPTER 6

Document Filtering

This chapter will demonstrate how to classify documents based on their contents, a very practical application of machine intelligence and one that is becoming more widespread. Perhaps the most useful and well-known application of document filtering is the elimination of spam. A big problem with the wide availability of email and the extremely low cost of sending email messages is that anyone whose address gets into the wrong hands is likely to receive unsolicited commercial email messages, making it difficult for them to read the messages that are actually of interest.

- Programming Collective Intelligence: Building Smart Web 2.0 Applications *T. Segaran*.

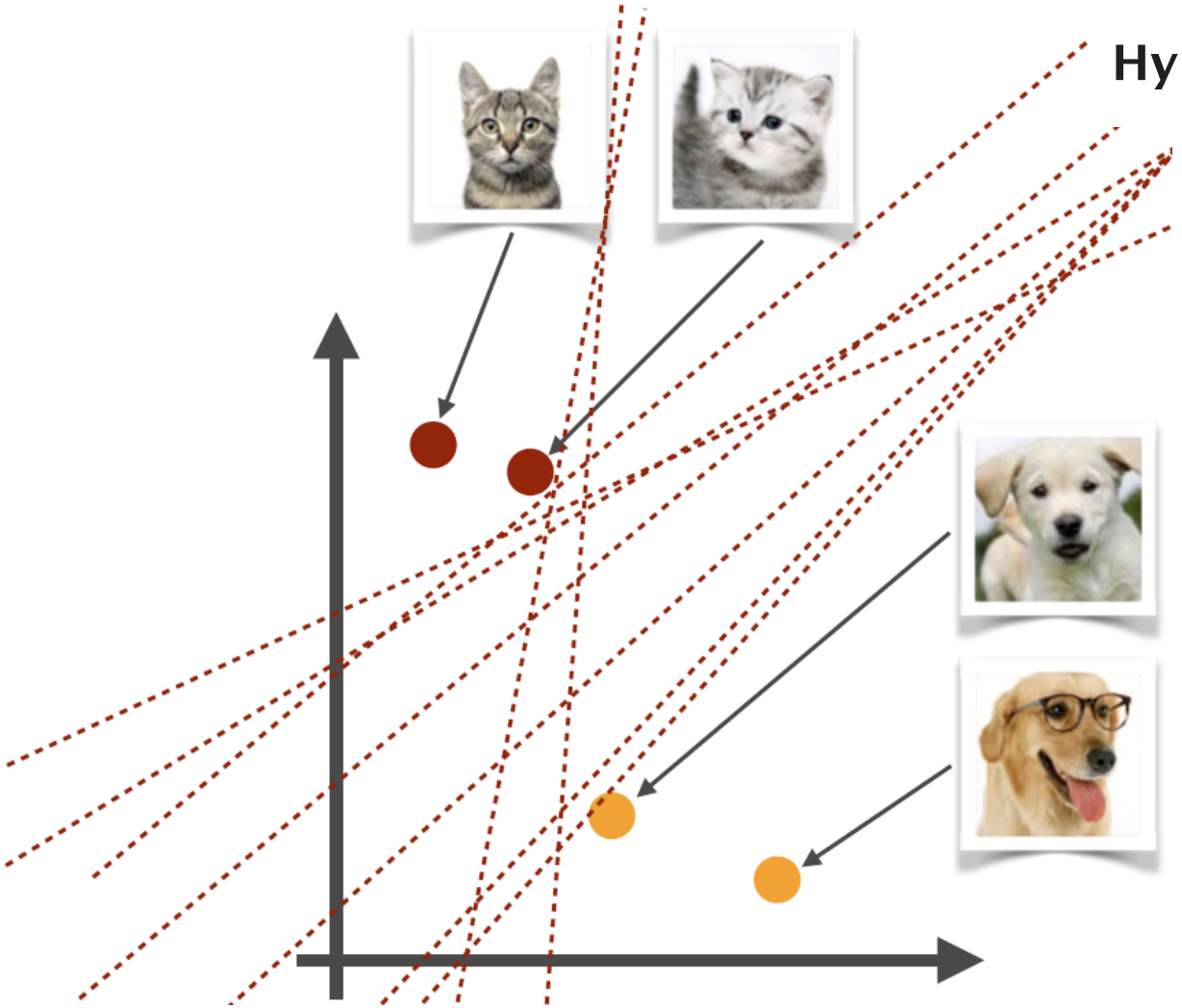
Document Filtering – **Overview (1/3)**



*Linear classifiers try to learn a **hyperplane** that separates two classes in feature space with **minimum error***

Credit: Jon Hare

Document Filtering – **Overview (2/3)**

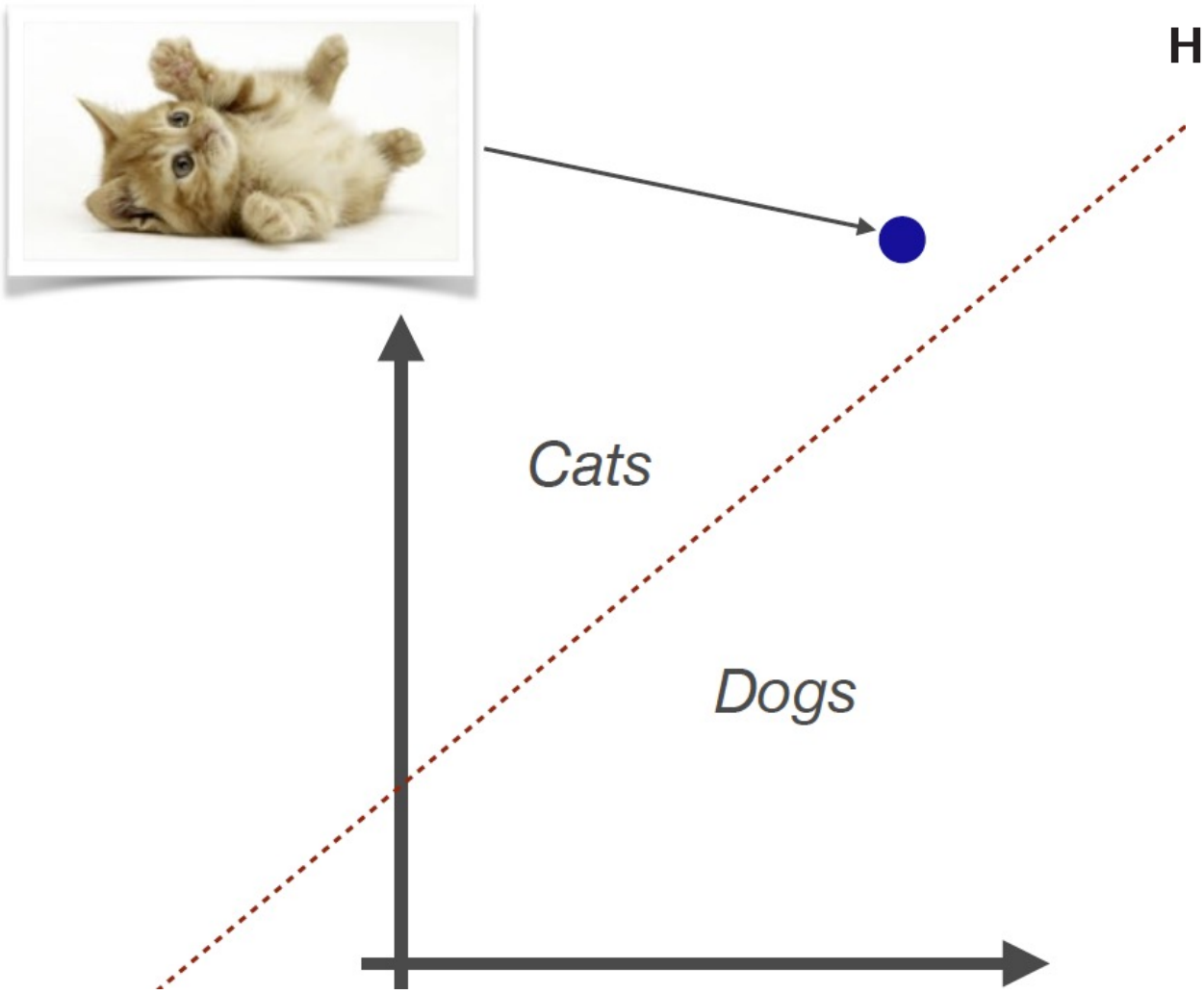


Hyperplanes

Lots of hyperplanes to choose from… different linear classification algorithms apply differing constraints when learning the classifier

Credit: Jon Hare

Document Filtering – **Overview (3/3)**



Hyperplane

To classify a new image, you just need to check what side of the hyperplane it is on

Credit: Jon Hare

Document Filtering – **Learning Outcomes**

- **LO1**: Demonstrate an understanding of the fundamental concepts and approaches for document filtering, such as: (exam)
  - Understanding the basic ideas behind Naive Bayes and Fisher's methods
  - Applying Naïve Bayes and Fisher's Methods to classify documents as spam or not spam
  - Discussing the pros and cons of using Naive Bayes vs. Fisher's methods for document filtering
- **LO2**: Implement the learned algorithms for document filtering (course work)

Assessment hints: Multi-choice Questions (single answer: concepts, calculation etc)

- *Textbook Exercises: textbooks (Programming + Mining)*
- *Other Exercises: https://www-users.cse.umn.edu/~kumar001/dmbook/sol.pdf*
- *ChatGPT or other AI-based techs*

Document Filtering – Introduction

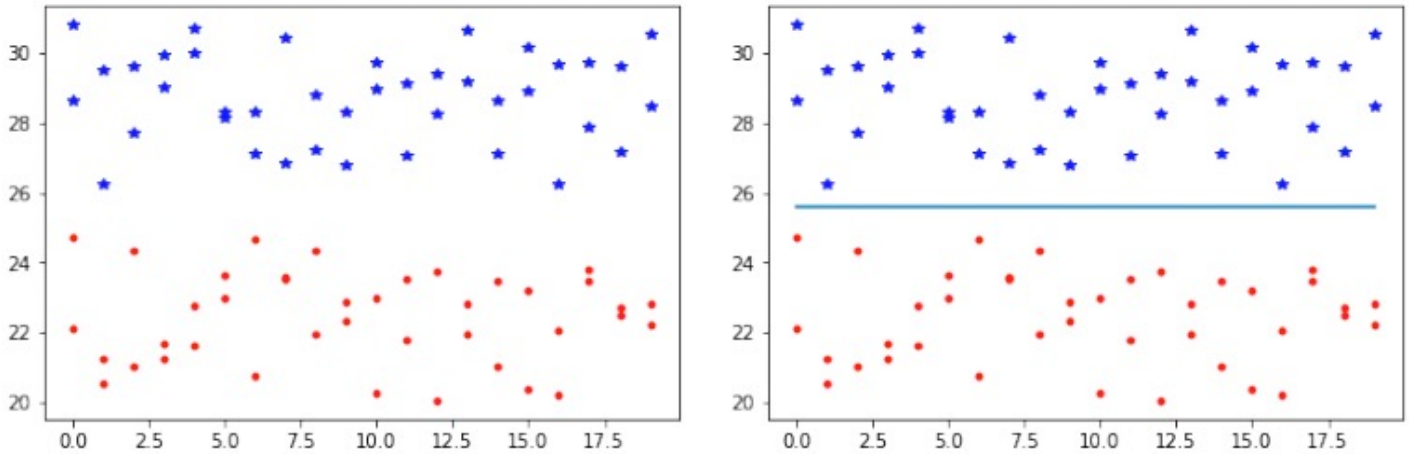
Document filtering can be accomplished by a range of approaches.

- Supervised Machine Learning - Classification
- Naïve Bayes
- Fisher's Method
- Feature Engineering

Credit: Jo Grundy

Document Filtering – Classification

Linear classifiers:



Separate different groups using a boundary, usually a hyperplane through featurespace, minimising error.

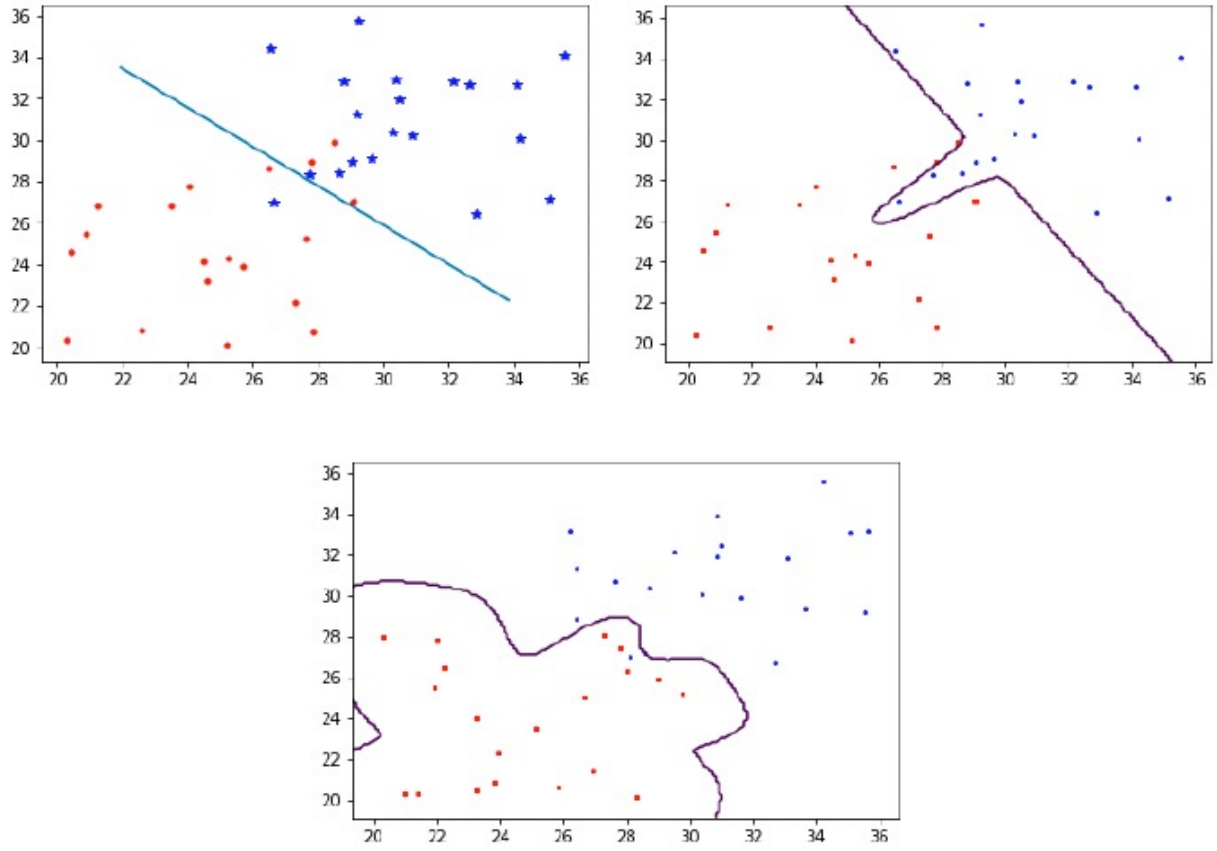
Different algorithms will chose the boundary dependent on different constraints.

This used a simple distance to mean classifier, that the Bayesian Decision Boundary simplifies to when the data is isotropic

Credit: Jo Grundy

Document Filtering – Classification

Non linear binary classifiers can work when the data is not linearly separable



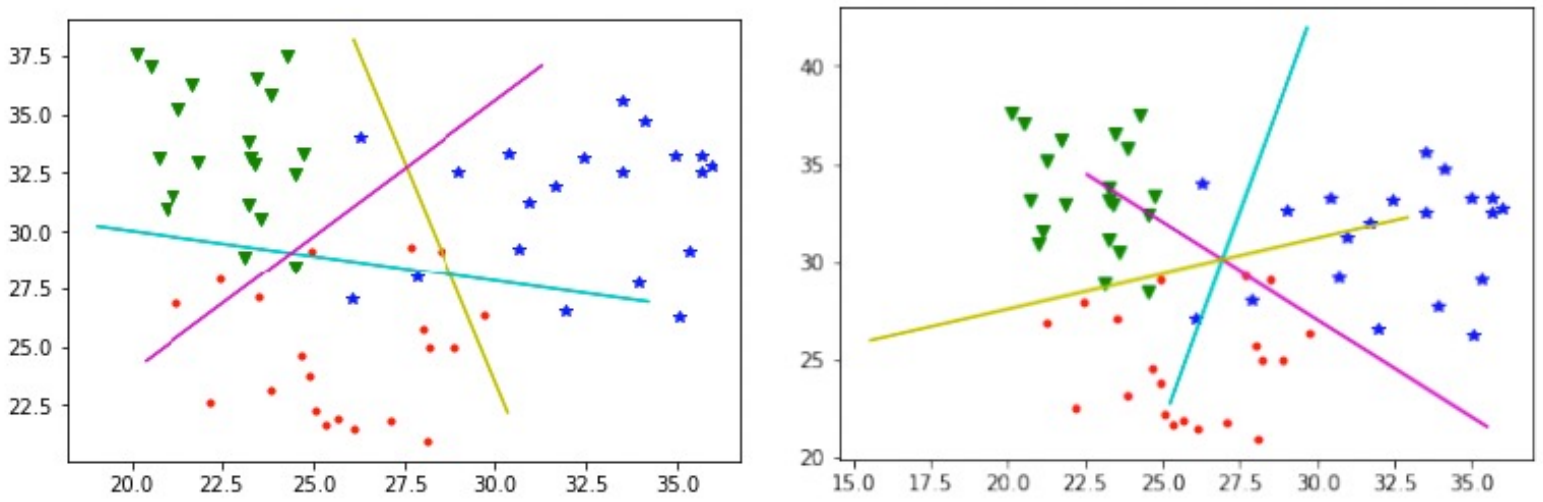
but you do need to watch out for overfitting

Credit: Jo Grundy

Document Filtering – Classification

Linear classifiers are binary classifiers.
How do you do multiclass classification using linear classifiers?

- One vs All - one classifier per class
- One vs One - K(K-1)/2 classifiers



One vs. All , One vs. One

Credit: Jo Grundy

Document Filtering – Spam Filters

Problem statement: Spam Filter
Need to classify if email is *spam* or *ham*
Early attempts used rules:
i.e. it is spam if it has:

- Too many capitals
- The word viagra or penis
- Garish colors in embedded html
- Email only has an embedded picture

Problems..?

- Some people like to use uppercase
- Spammers learn rules and get round them
- No personalisation
- What if the user wants to buy viagra?

Solution:

Credit: Jo Grundy

Document Filtering – Spam Filters

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Problems..?

- Some people like to use uppercase
- Spammers learn rules and get round them
- No personalisation
- What if the user wants to buy viagra?

Solution: use Machine Learning to build personalised spam filters

Credit: Jo Grundy

Document Filtering – Naïve Bayes

Start with *bag of words*

- simple tokenisation: split on non-letters
- simple pre-processing: convert all to lower case
- count only presence or absence of term

Make a table counting the number of times a term has appeared for each category

	money	viagra	tea	you	dear	...	Total
Spam	15	8	0	19	15	...	30
Ham	2	0	15	20	12	...	70

Count up the total number of documents

Credit: Jo Grundy

Document Filtering – Naïve Bayes

Now work out the conditional probability, i.e. the probability of a feature given a category:

If n_c is the number of documents in a category, and n_{fc} is the number of documents with feature f in category c..

$$p(f|c) = \frac{n_{fc}}{n_c}$$

	money	viagra	tea	you	dear	...	Total
Spam	15	8	0	19	15	...	30
Ham	2	0	15	20	12	...	70

Using the data above:
calculate $p(\text{“}viagra\text{”}|Spam)$

Credit: Jo Grundy

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Using the data above:
calculate $p(\text{“}viagra\text{”}|Spam) = 8/30 \approx 0.27$
calculate $p(\text{“}tea\text{”}|Ham)$

Credit: Jo Grundy

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calculate $p(\text{“}viagra\text{”}|Spam) = 8/30 \approx 0.27$
calculate $p(\text{“}tea\text{”}|Ham) = 15/70 \approx 0.21$.. but..
calculate $p(\text{“}tea\text{”}|Spam)$

Credit: Jo Grundy

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Using the data above:
calculate $p(\text{“}viagra\text{”}|Spam) = 8/30 \approx 0.27$
calculate $p(\text{“}tea\text{”}|Ham) = 15/70 \approx 0.21$.. but..
calculate $p(\text{“}tea\text{”}|Spam) = 0/30 = 0$!.. does this make sense?

Credit: Jo Grundy

Document Filtering – Naïve Bayes

Smoothing probability estimates

Should "tea" *never* be expected to appear in Spam documents?

Need a better way to estimate the conditional probability that accounts for infrequently seen features (sample size too small)

Credit: Jo Grundy

Document Filtering – Naïve Bayes

Smoothing probability estimates

Should "tea" *never* be expected to appear in Spam documents?

Need a better way to estimate the conditional probability that accounts for infrequently seen features (sample size too small)

We introduce an *assumed* probability

- where there is little evidence
- can be based on some evidence

Produce a weighted estimate for the conditional probability based on the assumed and the raw computed probability

Credit: Jo Grundy

Document Filtering – Naïve Bayes

Using Bayesian Statistics, assuming that random variables are drawn from probability distributions rather than point samples

In this case, Spam/Ham classification for a feature f is binomial with a *beta* distributed **prior**

$$p_w(f|c) = \frac{weight \times assumed + count \times p_{raw}(f|c)}{count + weight}$$

where *count* is the number of times feature f occurs across all categories

Note: You can use Naïve Bayes with a Bayesian approach or with a frequentist (MLE) approach.

Credit: Jo Grundy

Document Filtering – Naïve Bayes

However the conditional probability of the whole document is required

To do this we assume that all features are independent of each other.

This is what makes it Naïve Bayes

In this case the *features* are words, and as certain words are very likely to appear together this assumption is false. However in practice, it doesn't matter.

It will still work even if incorrect!

Credit: Jo Grundy

Document Filtering – Naïve Bayes

The Naïve assumption allows the conditional probability to be expressed as the product of all the conditional feature probabilities

$$p(d|c) = \prod_{f \in d} p(f|c)$$

This is the **likelihood** of the document given a category.

Posterior $\propto$ Likelihood Prior

Naive Bayes rules

$$P(c|d) = \frac{P(d|c)\,P(c)}{p(d)}$$

- P(c|d) = conditional probability of c given d (Posterior)
- P(d|c) = conditional probability of d given c (Likelihood)
- P(c) = prior probability of hypothesis/class c (Prior)
- P(d) = prior probability of data d (Evidence)

Thomas Bayes (1702–1761)

Credit: Jo Grundy

Document Filtering – Naïve Bayes

The Naïve assumption allows the conditional probability to be expressed as the product of all the conditional feature probabilities

$$p(d|c) = \prod_{f \in d} p(f|c)$$

This is the **likelihood** of the document given a category.

Posterior $\propto$ Likelihood Prior

Naive Bayes rules

$$P(c|d) = \frac{P(d|c)\,P(c)}{p(d)}$$

The **prior** can be calculated:

- Empirically, using the total No. docs in c divided by the total number
- or assuming all classes to be equally probably

$p(d)$ is constant, so therefore irrelevant, as same for all categories

Thomas Bayes (1702–1761)

Credit: Jo Grundy

Document Filtering – Naïve Bayes

The Naïve assumption allows the conditional probability to be expressed as the product of all the conditional feature probabilities

$$p(d|c) = \prod_{f \in d} p(f|c)$$

This is the **likelihood** of the document given a category.

When implementing, the product of a lot of very small numbers could lead to *floating point underflow*, so we take the logs and sum instead.

$$\log(p(c|d)) \propto \log(p(c)) + \sum_{f \in d} \log(p(f|c))$$

Credit: Jo Grundy

Document Filtering – Naïve Bayes

posterior $\propto$ likelihood $\times$ prior

$$\therefore p(c|d) \propto p(d|c) \times p(c)$$

$p(c|d)$ can be calculated for all categories using this formula
The most likely category is thus assigned to the document, i.e. with the largest $p(c|d)$. This is **maximum a posteriori**, MAP, and assumes the categories are equal.

In the case of Spam/Ham this isn't true, the cost of misclassifying a good email as Spam is much higher than misclassifying a Spam email as Ham.

Credit: Jo Grundy

Document Filtering – Naïve Bayes

Could require a higher ratio to classify..

$$if \quad \frac{p(Spam|d)}{p(Ham|d)} > 3 \quad then \quad Spam$$

Credit: Jo Grundy

Document Filtering – Fisher's Method

Naïve Bayes: uses feature likelihoods to compute whole document probability

Fisher's Method

- calculates probability of each category for each feature $p(c|f)$
- tests to see if combined probabilities are more or less likely than a random

This assumes independence of features

Credit: Jo Grundy

Document Filtering – Fisher's Method

To calculate category probabilities $p(c|f)$ for given feature:
Can use Bayes' Extended form, but need $P(c)$ for all c

$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{\sum_j P(B|A_j)P(A_j)}$$

$P(c)$ can be estimated from the data, or from an unbiased estimate, all $P(c)$ equally likely.

Credit: Jo Grundy

Document Filtering – Fisher's Method

$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{\sum_j P(B|A_j)P(A_j)}$$

For a Spam/Ham classifier, there is no *a priori* reason to assume one or the other.

$$P(c) = P(Ham) = P(Spam) = 0.5$$

$$\therefore P(c|f) = \frac{P(f|c)}{(P(f|Ham) + P(f|Spam))}$$

Credit: Jo Grundy

Document Filtering – Fisher's Method

Fisher's method combines k probabilities ("p-values") $P(c = C|f_k)$ from each test in to a single test statistic, X^2

$$X^2_{2k} \sim -2 \sum \ln(p(c = C|f_i))$$

if the p-values are independent, this X^2 statistic will follow a *chi-squared* distribution in $2k$ degrees of freedom

So we can calculate a combined p-value

$$p_C = K^{-1}(-2 \sum_{i=1}^{k} \ln(p(c = C|f_i)), 2k) = K^{-1}(-2 \ln(\prod_{i=1}^{k} p(c = C|f_i)), 2k)$$

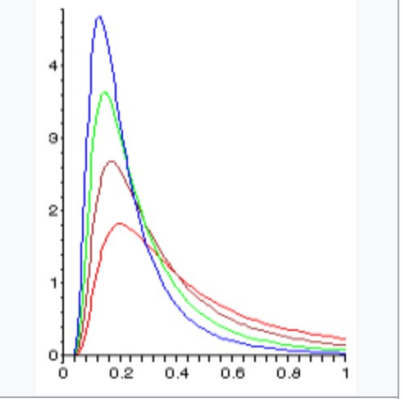
where K^{-1} is the inverse chi-squared function

PDF	$\frac{2^{-\nu/2}}{\Gamma(\nu/2)} x^{-\nu/2-1} e^{-1/(2x)}$

Parameters	$\nu > 0$

Inverse-chi-squared

Probability density function



Cumulative distribution function

https://en.wikipedia.org

https://en.wikipedia.org

Credit: Jo Grundy

Document Filtering – Fisher's Method

Making classifications

$$I = \frac{1 + p_{Spam} - p_{Ham}}{2}$$

I tends to 1 if document is Spam, and 0 if it is Ham.

Credit: Jo Grundy

Document Filtering – Improving Text Features

Feature Engineering:

In email, there are *Fields*

- sender; to; cc;
- title; subject; body

These can be used as separate features

Credit: Jo Grundy

Document Filtering – Improving Text Features

Spam emails may contain lots of capitals, so a new feature can be engineered to measure this

e.g. if more than 30% of words are uppercase, then record a virtual 'uppercase' feature..

	money	viagra	tea	you	dear	...	v. upper	Total
Spam	15	8	0	19	15	...	5	30
Ham	2	0	15	20	12	...	0	70

Credit: Jo Grundy

Document Filtering – Improving Text Features

N-Grams

Bag of words loses the order and context the words are in, so instead of looking at just individual words, we can use pairs, or triplets (n=2, 3) of words as a base feature.
Generally these are called $n-grams$

"The quick brown fox jumped over the lazy dog"
becomes:

'The quick" "quick brown" "brown fox" "fox jumped" "jumped over" "over the" "the lazy" "lazy dog"

Credit: Jo Grundy

Document Filtering – Improving Text Features

Can we do better?

Natural Language Processing

- POS - Part of Speech tagging

```
"The quick brown fox jumped over the lazy dog"

[('The', 'DT'), ('quick', 'JJ'), ('brown', 'NN'),
('fox', 'NN'), ('jumped', 'VBD'), ('over', 'IN'),
('the', 'DT'), ('lazy', 'JJ'), ('dog', 'NN')]
```

" The quick brown fox jumped over the lazy dog "

ipynb demo

https://github.com/zhiwu-huang/Data-Mining-Demo-Code-18-19

Credit: Jo Grundy

Document Filtering – Improving Text Features

- NE - Named entity extraction

  "but unfortunately for MSC Bellissima, the British weather intervened."

  but/CC

  unfortunately/RB

  for/IN

  (ORGANIZATION MSC/NNP Bellissima/NNP)

  the/DT

  (GPE British/JJ)

  weather/NN

  intervened/VBD

Credit: Jo Grundy

Document Filtering – Improving Text Features

Using these tools we can get ≈ 91% accuracy for POS tagging

State of the art is close to 97% accurate.

Natural Language Processing is **hard**!

More accurate, robust NLP is shallow
i.e. superficial analysis, not really understanding sentence

ChatGPT

Autoregressive Language Models

Simple, Old idea. Complete the sentence *"The mouse ate the"* ranked by probability learned from the corpus.

p("the", "mouse", "ate, "the", "cheese") = 0.10
p("the", "mouse", "ate, "the", "mouse") = 0.01
p("the", "mouse", "ate, "the", "house") = 0.0001

Neural Language Models.

- **Neural nets** "compactly" represent that probability function

Credit: Jo Grundy, and Percy from Stanford

University of Southampton

Document Filtering – Summary

Learning models to categorise data is a core part of data mining

- Many supervised machine learning techniques can be used
- For Spam/Ham, probabilistic approaches work well as:
  - easy to implement
  - interpretable
  - computationally efficient
  - online
  - .. but assuming independence of features (naïve) can be problematic

Choice of features is key

Credit: Jo Grundy