Day 6: Classification and Machine Learning

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Today's Road Map

The Naive Bayes Classifier

The k-Nearest Neighbour Classifier

Support Vector Machines (SVMs)

Assessing the reliability of a training set

Evaluating classification: Precision and recall

Lab session: Classifying Text Using `quanteda`

THE NAIVE BAYES CLASSIFIER

Prior probabilities and updating

A test is devised to automatically flag racist news stories.

- 1% of news stories in general have racist messages
- 80% of racist news stories will be flagged by the test
- 10% of non-racist stories will also be flagged

We run the test on a new news story, and it is *flagged as* racist.

Question: What is probability that the story is *actually* racist?

Any guesses?

Prior probabilities and updating

- What about without the test?
  - Imagine we run 1,000 news stories through the test
  - We expect that 10 will be racist
- With the test, we expect:
  - Of the 10 found to be racist, 8 should be flagged as racist
  - Of the 990 non-racist stories, 99 will be wrongly flagged as racist
  - That's a total of 107 stories flagged as racist
- So: the updated probability of a story being racist, conditional on being flagged as racist, is $\frac{8}{107} = 0.075$
- The *prior* probability of 0.01 is updated to only 0.075 by the positive test result

This is an example of Bayes' Rule:

$$P(R=1|T=1) = \frac{P(T=1|R=1)P(R=1)}{P(T=1)}$$

Multinomial Bayes model of Class given a Word

Consider J word types distributed across I documents, each assigned one of K classes.

At the word level, Bayes Theorem tells us that:

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j)}$$

For two classes, this can be expressed as

$$= \frac{P(w_j|c_k)P(c_k)}{P(w_j|c_k)P(c_k) + P(w_j|c_{\neg k})P(c_{\neg k})} \tag{1}$$

Classification as a goal

- Machine learning focuses on identifying classes (classification), while social science is typically interested in locating things on latent traits (scaling)
- One of the simplest and most robust classification methods is the "Naive Bayes" (NB) classifier, built on a Bayesian probability model
- The class predictions for a collection of words from NB are great for classification, but useless for scaling
- But intermediate steps from NB turn out to be excellent for scaling purposes, and identical to Laver, Benoit and Garry's "Wordscores"
- Applying lessons from machine to learning to supervised scaling, we can
  - Apply classification methods to scaling
  - improve it using lessons from machine learning

Supervised v. unsupervised methods compared

- The goal (in text analysis) is to differentiate *documents* from one another, treating them as “bags of words”
- Different approaches:
  - *Supervised methods* require a training set that exmplify constrasting classes, identified by the researcher
  - *Unsupervised methods* scale documents based on patterns of similarity from the term-document matrix, without requiring a training step
- Relative advantage of supervised methods:
  You already know the dimension being scaled, because you set it in the training stage
- Relative disadvantage of supervised methods:
  You *must* already know the dimension being scaled, because you have to feed it good sample documents in the training stage

Supervised v. unsupervised methods: Examples

- General examples:
  - Supervised: Naive Bayes, k-Nearest Neighbor, Support Vector Machines (SVM)
  - Unsupervised: correspondence analysis, IRT models, factor analytic approaches
- Political science applications
  - Supervised: Wordscores (LBG 2003); SVMs (Yu, Kaufman and Diermeier 2008); Naive Bayes (Evans et al 2007)
  - Unsupervised "Wordfish" (Slapin and Proksch 2008); Correspondence analysis (Schonhardt-Bailey 2008); two-dimensional IRT (Monroe and Maeda 2004)

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Multinomial Bayes model of Class given a Word

Class-conditional word likelihoods

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j|c_k)P(c_k) + P(w_j|c_{\neg k})P(c_{\neg k})}$$

- The word likelihood within class
- The maximum likelihood estimate is simply the proportion of times that word j occurs in class k, but it is more common to use Laplace smoothing by adding 1 to each oberved count within class

Multinomial Bayes model of Class given a Word

Word probabilities

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j)}$$

- This represents the word probability from the training corpus
- Usually uninteresting, since it is constant for the training data, but needed to compute posteriors on a probability scale

Multinomial Bayes model of Class given a Word

Class prior probabilities

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j|c_k)P(c_k) + P(w_j|c_{\neg k})P(c_{\neg k})}$$

- This represents the class prior probability
- Machine learning typically takes this as the document frequency in the training set
- This approach is flawed for scaling, however, since we are scaling the latent class-ness of an unknown document, not predicting class – uniform priors are more appropriate

Multinomial Bayes model of Class given a Word
Class posterior probabilities

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j|c_k)P(c_k) + P(w_j|c_{\neg k})P(c_{\neg k})}$$

- This represents the posterior probability of membership in class k for word j
- Under *certain conditions*, this is identical to what LBG (2003) called P_{wr}
- Under those conditions, the LBG "wordscore" is the linear difference between $P(c_k|w_j)$ and $P(c_{\neg k}|w_j)$

Moving to the document level

- The “Naive” Bayes model of a joint document-level class posterior assumes conditional independence, to multiply the word likelihoods from a “test” document, to produce:

$$P(c|d) = P(c) \prod_j \frac{P(w_j|c)}{P(w_j)}$$

- This is why we call it “naive”: because it (wrongly) assumes:
  - *conditional independence* of word counts
  - *positional independence* of word counts

Naive Bayes Classification Example

(From Manning, Raghavan and Schütze, *Introduction to Information Retrieval*)

► **Table 13.1** Data for parameter estimation examples.

	docID	words in document	in $c = China$?
training set	1	Chinese Beijing Chinese	yes
	2	Chinese Chinese Shanghai	yes
	3	Chinese Macao	yes
	4	Tokyo Japan Chinese	no
test set	5	Chinese Chinese Chinese Tokyo Japan	?

Naive Bayes Classification Example

Example 13.1: For the example in Table 13.1, the multinomial parameters we need to classify the test document are the priors $\hat{P}(c) = 3/4$ and $\hat{P}(\overline{c}) = 1/4$ and the following conditional probabilities:

$$\begin{aligned}
\hat{P}(\text{Chinese}|c) &= (5+1)/(8+6) = 6/14 = 3/7 \\
\hat{P}(\text{Tokyo}|c) = \hat{P}(\text{Japan}|c) &= (0+1)/(8+6) = 1/14 \\
\hat{P}(\text{Chinese}|\overline{c}) &= (1+1)/(3+6) = 2/9 \\
\hat{P}(\text{Tokyo}|\overline{c}) = \hat{P}(\text{Japan}|\overline{c}) &= (1+1)/(3+6) = 2/9
\end{aligned}$$

The denominators are $(8+6)$ and $(3+6)$ because the lengths of $text_c$ and $text_{\overline{c}}$ are 8 and 3, respectively, and because the constant B in Equation (13.7) is 6 as the vocabulary consists of six terms.

We then get:

$$\begin{aligned}
\hat{P}(c|d_5) &\propto 3/4 \cdot (3/7)^3 \cdot 1/14 \cdot 1/14 \approx 0.0003. \\
\hat{P}(\overline{c}|d_5) &\propto 1/4 \cdot (2/9)^3 \cdot 2/9 \cdot 2/9 \approx 0.0001.
\end{aligned}$$

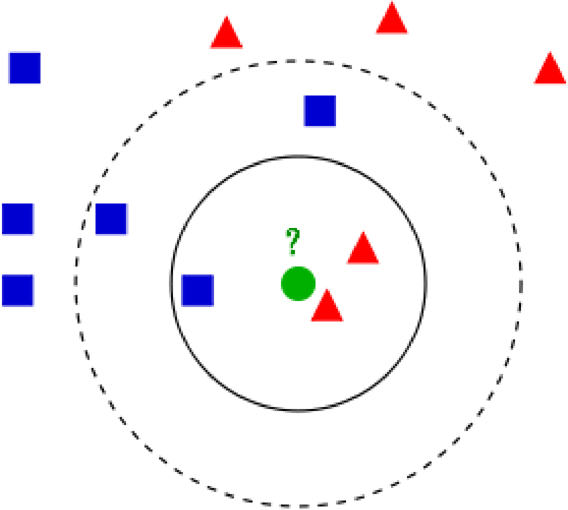
Thus, the classifier assigns the test document to c = *China*. The reason for this classification decision is that the three occurrences of the positive indicator Chinese in d_5 outweigh the occurrences of the two negative indicators Japan and Tokyo.

THE k-NN CLASSIFIER

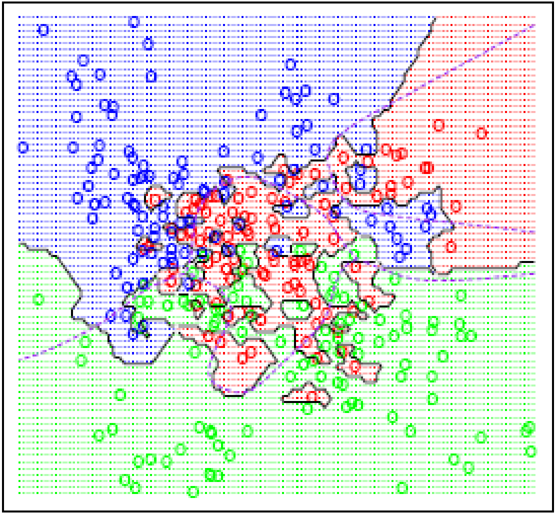
Other classification methods: *k*-nearest neighbour

- A non-parametric method for classifying objects based on the training examples taht are *closest* in the feature space
- A type of instance-based learning, or "lazy learning" where the function is only approximated locally and all computation is deferred until classification
- An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its k nearest neighbors (where k is a positive integer, usually small)
- Extremely *simple*: the only parameter that adjusts is k (number of neighbors to be used) - increasing k *smooths* the decision boundary

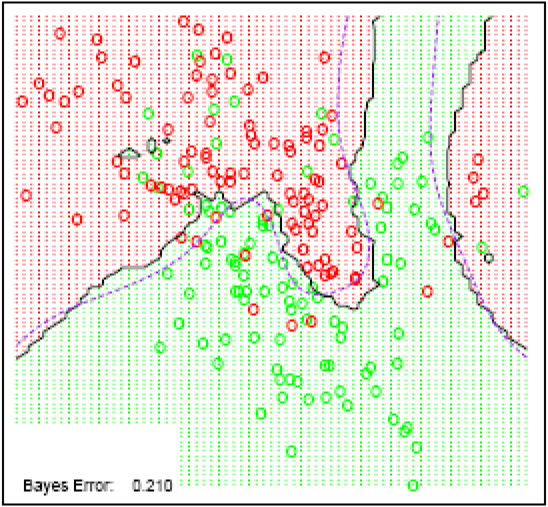
k-NN Example: Red or Blue?



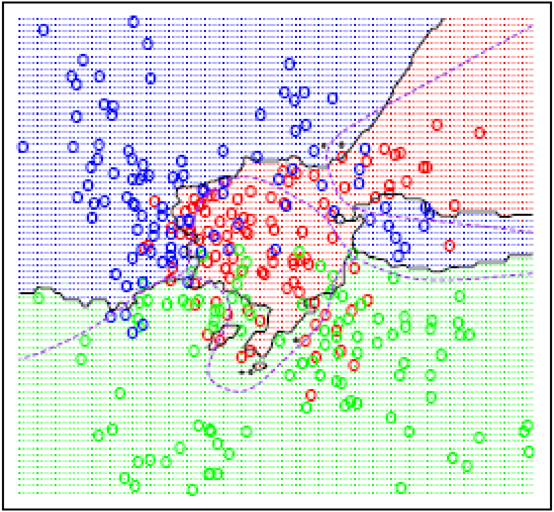
$k = 1$



$k = 7$



$k = 15$



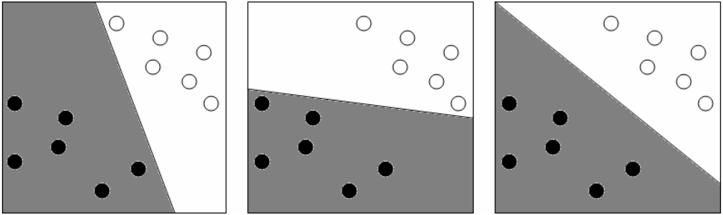
k-nearest neighbour issues: Dimensionality

- Distance usually relates to all the attributes and assumes all of them have the same effects on distance
- Misclassification may results from attributes not confirming to this assumption (sometimes called the "curse of dimensionality") – solution is to reduce the dimensions
- There are (many!) different *metrics* of distance

SUPPORT VECTOR MACHINES

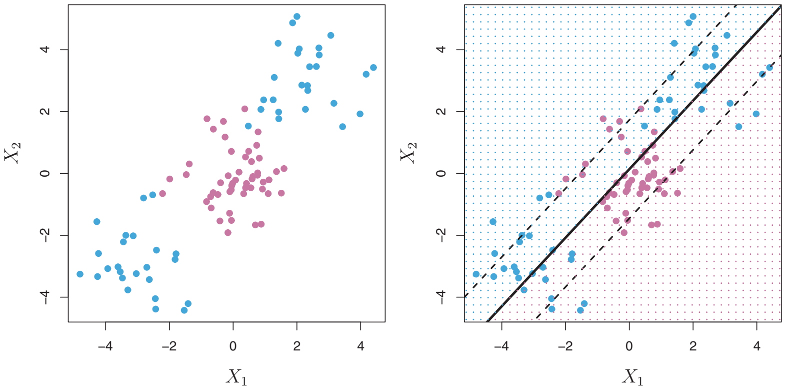
(Very) General overview to SVMs

- Generalization of maximal margin classifier
- The idea is to find the classification boundary that maximizes the distance to the marginal points

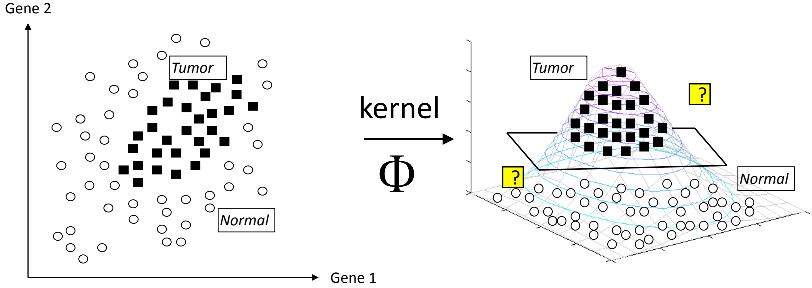


- Unfortunately MMC does not apply to cases with non-linear decision boundaries

No solution to this using support vector classifier



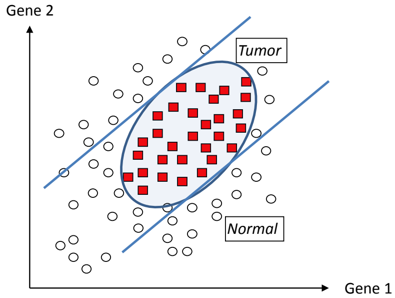
SVMs represent the data in a *higher* dimensional projection using a kernel, and bisect this using a hyperplane



Data is not linearly separable in the <u>input space</u>

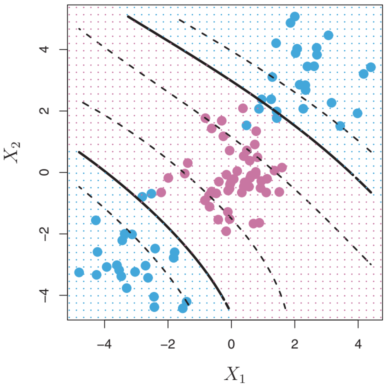
Data is linearly separable in the <u>feature space</u> obtained by a kernel

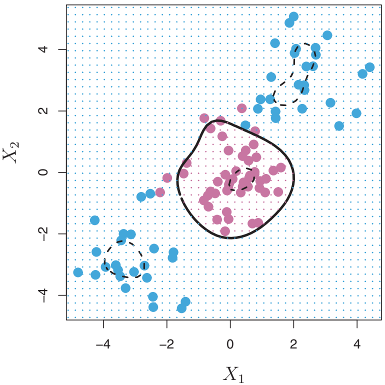
This is only needed when no linear separation plane exists - so not needed in second of these



Different "kernels" can represent different decision boundaries

- This has to do with different projections of the data into higher-dimensional space
- The mathematics of this are complicated but solveable as forms of optimization problems - but the kernel choice is a user decision





EVALUATING CLASSIFIER PERFORMANCE

Basic principles of machine learning: Generalization and overfitting

- Generalization: A classifier or a regression algorithm learns to correctly predict output from given inputs not only in previously seen samples but also in previously unseen samples
- Overfitting: A classifier or a regression algorithm learns to correctly predict output from given inputs in previously seen samples but fails to do so in previously unseen samples. This causes poor prediction/generalization.
- Goal is to maximize the frontier of precise identification of true condition with accurate recall

Precision and recall

- Same intuition as specificity and sensitivity earlier in course

		True condition	
		Positive	Negative
Prediction	Positive	True Positive	False Positive (Type I error)
	Negative	False Negative (Type II error)	True Negative

Precision and recall and related statistics

- Precision: $\frac{\text{true positives}}{\text{true positives} + \text{false positives}}$
- Recall: $\frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$
- Accuracy: $\frac{\text{Correctly classified}}{\text{Total number of cases}}$
- $F1 = 2\,\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$
  (the harmonic mean of precision and recall)

Example: Computing precision/recall

Assume:

- We have a corpus where 80 documents are really positive (as opposed to negative, as in sentiment)
- Our method declares that 60 are positive
- Of the 60 declared positive, 45 are actually positive

Solution:

$$\text{Precision} = (45/(45+15)) = 45/60 = 0.75$$
$$\text{Recall} = (45/(45+35)) = 45/80 = 0.56$$

Accuracy?

		True condition		
		Positive	Negative	
Prediction	Positive	45		60
	Negative			
		80		

add in the cells we can compute

		True condition		
		Positive	Negative	
Prediction	Positive	45	*15*	60
	Negative	*35*		
		80		

but need True Negatives and N to compute accuracy

		True condition		
		Positive	Negative	
Prediction	Positive	45	*15*	60
	Negative	*35*	**???**	
		80		

assume 10 True Negatives:

		True condition		
		Positive	Negative	
Prediction	Positive	45	*15*	60
	Negative	*35*	***10***	***45***
		80	***25***	***105***

$$\text{Accuracy} = (45 + 10)/105 \qquad = 0.52$$

$$\text{F1} = 2 * (0.75 * 0.56)/(0.75 + 0.56) \qquad = 0.64$$

now assume 100 True Negatives:

		True condition		
		Positive	Negative	
Prediction	Positive	45	*15*	60
	Negative	*35*	***100***	***135***
		80	***115***	***195***

$$\text{Accuracy} = (45 + 100)/195 = 0.74$$

$$\text{F1} = 2 * (0.75 * 0.56)/(0.75 + 0.56) = 0.64$$

RELIABILITY TESTING FOR THE TRAINING SET

How do we get "true" condition?

- In some domains: through more expensive or extensive tests
- In social sciences: typically by expert annotation or coding
- A scheme should be tested and reported for its reliability

Inter-rater reliability

Different types are distinguished by the way the reliability data is obtained.

Type	**Test Design**	**Causes of Disagreements**	Strength
Stability	test-retest	intraobserver inconsistencies	weakest
Reproducibility	test-test	intraobserver inconsistencies + interobserver disagreements	medium
Accuracy	test-standard	intraobserver inconsistencies + interobserver disagreements + deviations from a standard	strongest

Measures of agreement

- Percent agreement Very simple: (number of agreeing ratings) / (total ratings) * 100%
- Correlation
  - (usually) Pearson's r, aka product-moment correlation
  - Formula: $r_{AB} = \frac{1}{n-1} \sum_{i=1}^{n} \left(\frac{A_i - \bar{A}}{s_A} \right) \left(\frac{B_i - \bar{B}}{s_B} \right)$
  - May also be ordinal, such as Spearman's rho or Kendall's tau-b
  - Range is [0,1]
- Agreement measures
  - Take into account not only observed agreement, but also *agreement that would have occured by chance*
  - Cohen's κ is most common
  - Krippendorf's α is a generalization of Cohen's κ
  - Both range from [0,1]

Reliability data matrixes

Example here used binary data (from Krippendorff)

Article:	1	2	3	4	5	6	7	8	9	10
Coder A	1	1	0	0	0	0	0	0	0	0
Coder B	0	1	1	0	0	1	0	1	0	0

- A and B agree on 60% of the articles: 60% agreement
- Correlation is (approximately) 0.10
- Observed *dis*agreement: 4
- Expected *dis*agreement (by chance): 4.4211
- Krippendorff's $\alpha = 1 - \frac{D_o}{D_e} = 1 - \frac{4}{4.4211} = 0.095$
- Cohen's κ (nearly) identical