Introduction to Information Retrieval

http://informationretrieval.org

IIR 13: Text Classification & Naive Bayes

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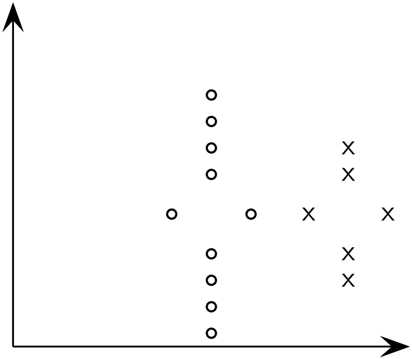
Overview

Outline

Relevance feedback: Basic idea

- The user issues a (short, simple) query.
- The search engine returns a set of documents.
- User marks some docs as relevant, some as nonrelevant.
- Search engine computes a new representation of the information need – should be better than the initial query.
- Search engine runs new query and returns new results.
- New results have (hopefully) better recall.

Rocchio illustrated



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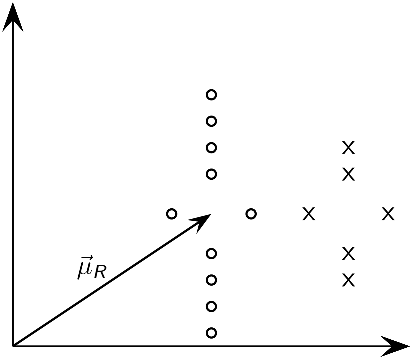

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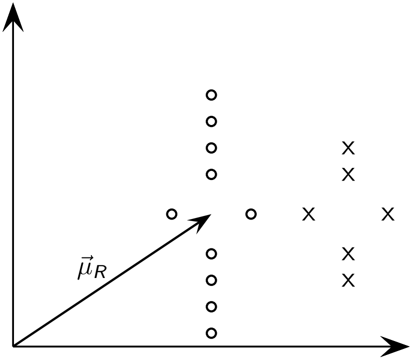

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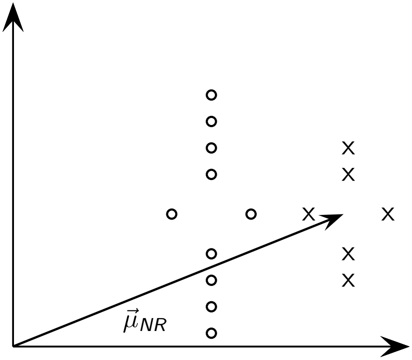

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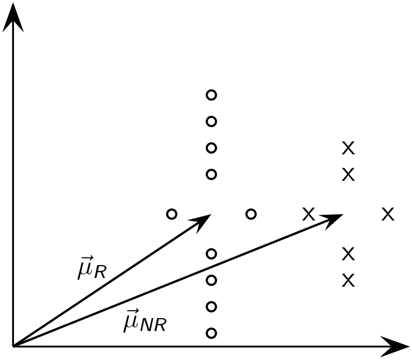

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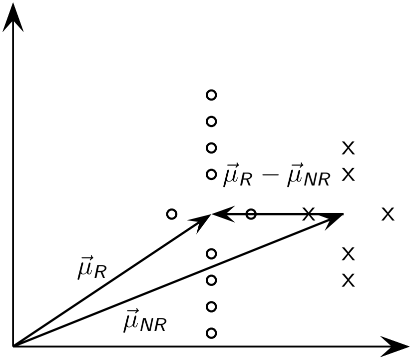

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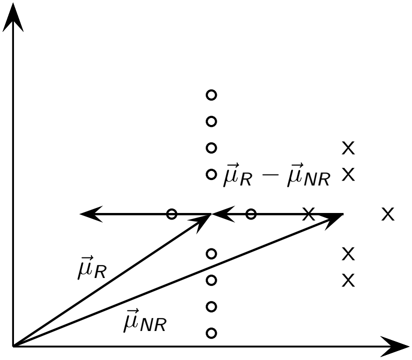

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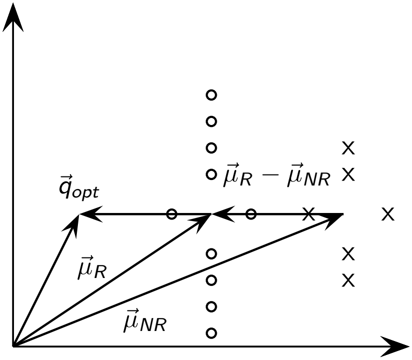

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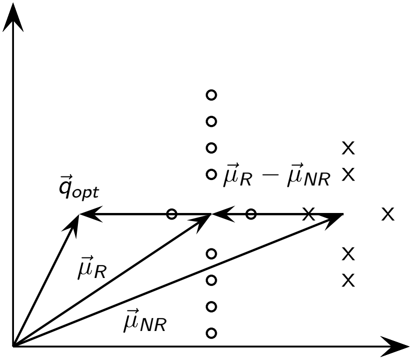

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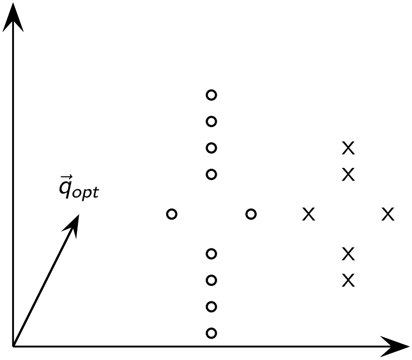

Types of query expansion

- Manual thesaurus (maintained by editors, e.g., PubMed)
- Automatically derived thesaurus (e.g., based on co-occurrence statistics)
- Query-equivalence based on query log mining (common on the web as in the "palm" example)

Query expansion at search engines

- Main source of query expansion at search engines: query logs
- Example 1: After issuing the query [herbs], users frequently search for [herbal remedies].
  - $\rightarrow$ "herbal remedies" is potential expansion of "herb".
- Example 2: Users searching for [flower pix] frequently click on the URL photobucket.com/flower. Users searching for [flower clipart] frequently click on the same URL.
  - $\rightarrow$ "flower clipart" and "flower pix" are potential expansions of each other.

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- Naive Bayes: simple baseline text classifier
- Theory: derivation of Naive Bayes classification rule & analysis
- Evaluation of text classification: how do we know it worked / didn't work?

Outline

A text classification task: Email spam filtering

```
From: ‘‘’’ <takworlld@hotmail.com>
Subject: real estate is the only way... gem  oalvgkay

Anyone can buy real estate with no money down

Stop paying rent TODAY !

There is no need to spend hundreds or even thousands for similar courses

I am 22 years old and I have already purchased 6 properties using the
methods outlined in this truly INCREDIBLE ebook.

Change your life NOW !

=================================================
Click Below to order:
http://www.wholesaledaily.com/sales/nmd.htm
=================================================
```

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Using a learning method or learning algorithm, we then wish to learn a classifier γ that maps documents to classes:

$$\gamma : \mathbb{X} \to \mathbb{C}$$

Formal definition of TC: Application/Testing

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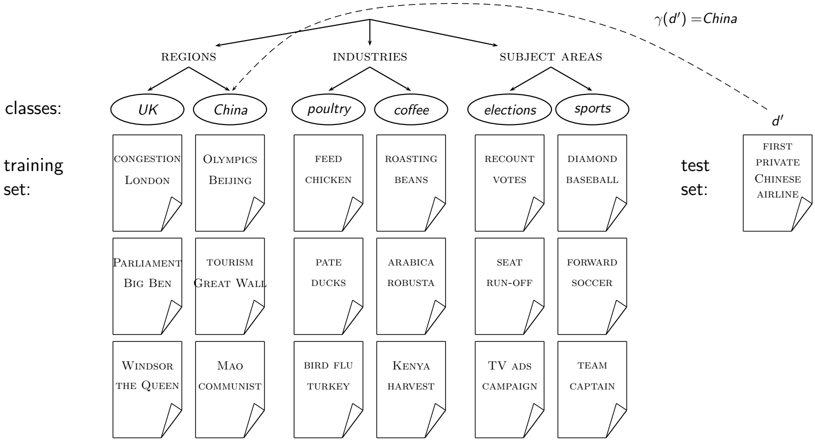
Given: a description $d \in \mathbb{X}$ of a document

Determine: $\gamma(d) \in \mathbb{C}$, that is, the class that is most appropriate for d

Topic classification



Exercise

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- Find examples of uses of text classification in information retrieval

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- Sentiment detection: is a movie or product review positive or negative (positive vs. negative)
- Topic-specific or *vertical* search – restrict search to a "vertical" like "related to health" (relevant to vertical vs. not)

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- Scaling manual classification is difficult and expensive.
- $\rightarrow$ We need automatic methods for classification.

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- Building and maintaining rule-based classification systems is cumbersome and expensive.

A Verity topic (a complex classification rule)

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```
comment line                 # Beginning of art topic definition
top-level topic              art ACCRUE
                                  /author = "fsmith"
topic definition modifiers        /date   = "30-Dec-01"
                                  /annotation = "Topic created
                                                  by fsmith"
subtopictopic                * 0.70 performing-arts ACCRUE
  evidencetopic              ** 0.50 WORD
  topicdefinition modifier        /wordtext = ballet
  evidencetopic              ** 0.50 STEM
  topicdefinition modifier        /wordtext = dance
  evidencetopic              ** 0.50 WORD
  topicdefinition modifier        /wordtext = opera
  evidencetopic              ** 0.30 WORD
  topicdefinition modifier        /wordtext = symphony
subtopic                     * 0.70 visual-arts ACCRUE
                             ** 0.50 WORD
                                  /wordtext = painting
                             ** 0.50 WORD
                                  /wordtext = sculpture
```

```
subtopic     * 0.70 film ACCRUE
             ** 0.50 STEM
                  /wordtext = film
subtopic     ** 0.50 motion-picture PHRAS
             *** 1.00 WORD
                  /wordtext = motion
             *** 1.00 WORD
                  /wordtext = picture
             ** 0.50 STEM
                  /wordtext = movie
subtopic     * 0.50 video ACCRUE
             ** 0.50 STEM
                  /wordtext = video
             ** 0.50 STEM
                  /wordtext = vcr
             # End of art topic
```

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- No free lunch: requires hand-classified training data
- But this manual classification can be done by non-experts.

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- $P(c)$ is the prior probability of c.
- If a document's terms do not provide clear evidence for one class vs. another, we choose the c with highest $P(c)$.

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- The best class is the most likely or maximum a posteriori (MAP) class c_{map}:

$$c_{\text{map}} = \arg\max_{c \in \mathbb{C}} \hat{P}(c|d) = \arg\max_{c \in \mathbb{C}} \ \hat{P}(c) \prod_{1 \leq k \leq n_d} \hat{P}(t_k|c)$$

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- Since $\log(xy) = \log(x) + \log(y)$, we can sum log probabilities instead of multiplying probabilities.
- Since log is a monotonic function, the class with the highest score does not change.
- So what we usually compute in practice is:

$$c_{\text{map}} = \arg\max_{c \in \mathbb{C}} [\log \hat{P}(c) + \sum_{1 \leq k \leq n_d} \log \hat{P}(t_k|c)]$$

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- We've made a Naive Bayes independence assumption here: $\hat{P}(t_k|c) = \hat{P}(t_k|c)$, independent of position

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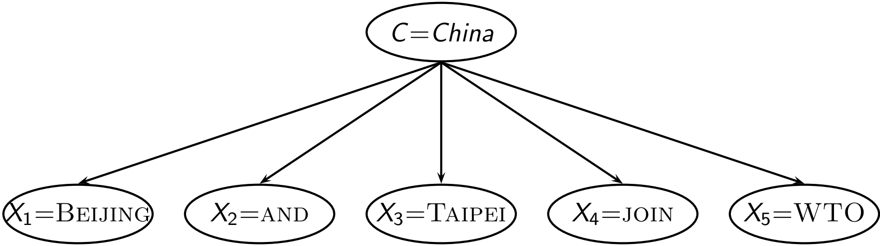

$$P(China|d) \propto P(China) \cdot P(\text{Beijing}|China) \cdot P(\text{and}|China) \cdot P(\text{Taipei}|China) \cdot P(\text{join}|China) \cdot P(\text{WTO}|China)$$

- If WTO never occurs in class China in the train set:

$$\hat{P}(\text{WTO}|China) = \frac{T_{China,\text{WTO}}}{\sum_{t' \in V} T_{China,t'}} = \frac{0}{\sum_{t' \in V} T_{China,t'}} = 0$$

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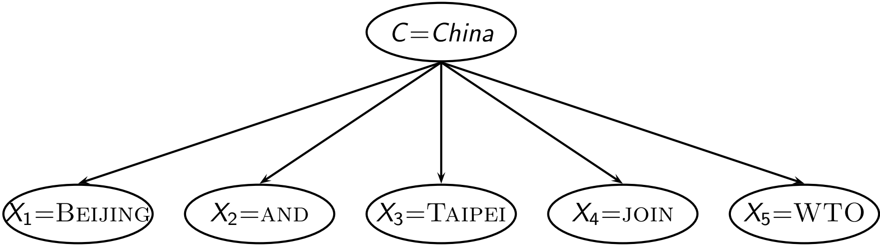

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\end{aligned}
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- $\rightarrow$ We will get $P(China|d) = 0$ for any document that contains WTO!

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- Now: Add one to each count to avoid zeros:

$$\hat{P}(t|c) = \frac{T_{ct} + 1}{\sum_{t' \in V}(T_{ct'} + 1)} = \frac{T_{ct} + 1}{(\sum_{t' \in V} T_{ct'}) + B}$$

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- B is the number of bins – in this case the number of different words or the size of the vocabulary $|V| = M$

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- For a new document, for each class, compute sum of (i) log of prior and (ii) logs of conditional probabilities of the terms

Naive Bayes: Summary

- Estimate parameters from the training corpus using add-one smoothing
- For a new document, for each class, compute sum of (i) log of prior and (ii) logs of conditional probabilities of the terms
- Assign the document to the class with the largest score

Naive Bayes: Training

Naive Bayes: Training

$\textsc{TrainMultinomialNB}(\mathbb{C}, \mathbb{D})$

$V \leftarrow \textsc{ExtractVocabulary}(\mathbb{D})$

$N \leftarrow \textsc{CountDocs}(\mathbb{D})$

for each $c \in \mathbb{C}$

do $N_c \leftarrow \textsc{CountDocsInClass}(\mathbb{D}, c)$

  $prior[c] \leftarrow N_c / N$

  $text_c \leftarrow \textsc{ConcatenateTextOfAllDocsInClass}(\mathbb{D}, c)$

  for each $t \in V$

  do $T_{ct} \leftarrow \textsc{CountTokensOfTerm}(text_c, t)$

  for each $t \in V$

  do $condprob[t][c] \leftarrow \frac{T_{ct}+1}{\sum_{t'}(T_{ct'}+1)}$

return $V, prior, condprob$

Naive Bayes: Testing

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$\textsc{ApplyMultinomialNB}(\mathbb{C}, V, \mathit{prior}, \mathit{condprob}, d)$

$W \leftarrow \textsc{ExtractTokensFromDoc}(V, d)$

for each $c \in \mathbb{C}$

do $\mathit{score}[c] \leftarrow \log \mathit{prior}[c]$

  for each $t \in W$

  do $\mathit{score}[c] += \log \mathit{condprob}[t][c]$

return $\arg\max_{c \in \mathbb{C}} \mathit{score}[c]$

Exercise: Estimate parameters, classify test set

	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	?

$$\hat{P}(c) = \frac{N_c}{N}$$

$$\hat{P}(t|c) = \frac{T_{ct} + 1}{\sum_{t' \in V}(T_{ct'} + 1)} = \frac{T_{ct} + 1}{(\sum_{t' \in V} T_{ct'}) + B}$$

(B is the number of bins – in this case the number of different words or the size of the vocabulary $|V| = M$)

$$c_{\text{map}} = \arg\max_{c \in \mathbb{C}} [\hat{P}(c) \cdot \prod_{1 \leq k \leq n_d} \hat{P}(t_k|c)]$$

Example: Parameter estimates

Example: Parameter estimates

Priors: $\hat{P}(c) = 3/4$ and $\hat{P}(\overline{c}) = 1/4$
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 is 6 as the vocabulary consists of six terms.

Example: Classification

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

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.

Time complexity of Naive Bayes

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mode	time complexity
training	$\Theta(\lvert\mathbb{D}\rvert L_{\mathsf{ave}} + \lvert\mathbb{C}\rvert\lvert V\rvert)$
testing	$\Theta(L_{\mathsf{a}} + \lvert\mathbb{C}\rvert M_{\mathsf{a}}) = \Theta(\lvert\mathbb{C}\rvert M_{\mathsf{a}})$

- L_{ave}: average length of a training doc, L_{a}: length of the test doc, M_{a}: number of distinct terms in the test doc, $\mathbb{D}$: training set, V: vocabulary, $\mathbb{C}$: set of classes

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- Generally: $\lvert\mathbb{C}\rvert\lvert V\rvert < \lvert\mathbb{D}\rvert L_{\text{ave}}$
- Test time is also linear (in the length of the test document).
- Thus: Naive Bayes is linear in the size of the training set (training) and the test document (testing). This is optimal.

Outline

1. Recap
2. Text classification
3. Naive Bayes
4. NB theory
5. Evaluation of TC

Naive Bayes: Analysis

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- Now we want to gain a better understanding of the properties of Naive Bayes.

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- We will formally derive the classification rule . . .
- . . . and make our assumptions explicit.

Derivation of Naive Bayes rule

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We want to find the class that is most likely given the document:

$$c_{\text{map}} = \underset{c \in \mathbb{C}}{\arg\max} \; P(c|d)$$

Apply Bayes rule $P(A|B) = \frac{P(B|A)P(A)}{P(B)}$:

$$c_{\text{map}} = \underset{c \in \mathbb{C}}{\arg\max} \; \frac{P(d|c)P(c)}{P(d)}$$

Drop denominator since $P(d)$ is the same for all classes:

$$c_{\text{map}} = \underset{c \in \mathbb{C}}{\arg\max} \; P(d|c)P(c)$$

Too many parameters / sparseness

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\begin{aligned}
c_{\text{map}} &= \underset{c \in \mathbb{C}}{\arg\max}\; P(d|c)P(c) \\
&= \underset{c \in \mathbb{C}}{\arg\max}\, P(\langle t_1, \ldots, t_k, \ldots, t_{n_d} \rangle | c)P(c)
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- This is the problem of data sparseness.

Naive Bayes conditional independence assumption

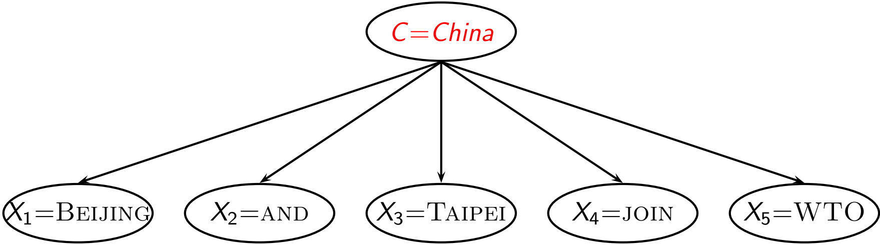
To reduce the number of parameters to a manageable size, we make the Naive Bayes conditional independence assumption:

$$P(d|c) = P(\langle t_1, \ldots, t_{n_d} \rangle | c) = \prod_{1 \leq k \leq n_d} P(X_k = t_k | c)$$

We assume that the probability of observing the conjunction of attributes is equal to the product of the individual probabilities $P(X_k = t_k|c)$.
Recall from earlier the estimates for these conditional probabilities: $\hat{P}(t|c) = \frac{T_{ct}+1}{(\sum_{t' \in V} T_{ct'})+B}$

Generative model

Generative model



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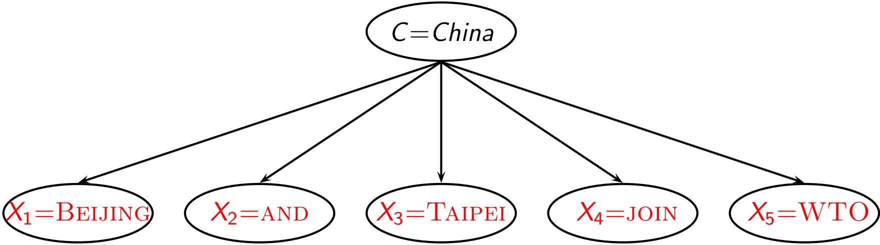

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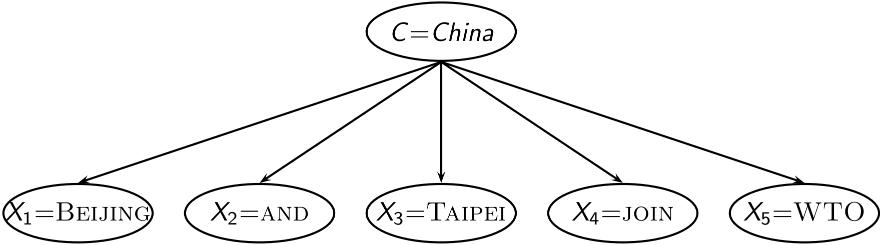

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- Generate a class with probability $P(c)$
- Generate each of the words (in their respective positions), conditional on the class, but independent of each other, with probability $P(t_k|c)$
- To classify docs, we "reengineer" this process and find the class that is most likely to have generated the doc.

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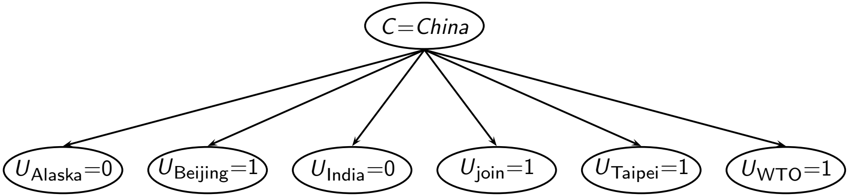
- For example, for a document in the class *UK*, the probability of generating QUEEN in the first position of the document is the same as generating it in the last position.
- The two independence assumptions amount to the bag of words model.

A different Naive Bayes model: Bernoulli model



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- Exercise
  - Examples for why conditional independence assumption is not really true?
  - Examples for why positional independence assumption is not really true?
- How can Naive Bayes work if it makes such inappropriate assumptions?

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true probability $P(c\|d)$	0.6	0.4	c_1
$\hat{P}(c) \prod_{1 \leq k \leq n_d} \hat{P}(t_k\|c)$	0.00099	0.00001	
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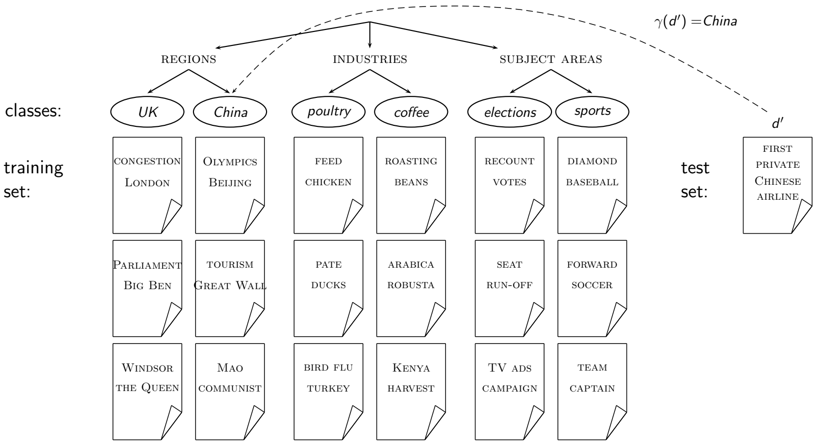
- Very fast
- Low storage requirements

Outline

Evaluation on Reuters



Example: The Reuters collection

symbol	statistic	value
N	documents	800,000
L	avg. # word tokens per document	200
M	word types	400,000

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type of class	number	examples
region	366	UK, China
industry	870	poultry, coffee
subject area	126	elections, sports

A Reuters document

A Reuters document

REUTERS

You are here: Home > News > Science > Article

Go to a Section: U.S. International Business Markets Politics Entertainment Technology Sports Oddly Enoug

Extreme conditions create rare Antarctic clouds

Tue Aug 1, 2006 3:20am ET

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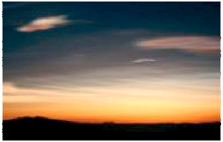

[-] Text [+]

SYDNEY (Reuters) - Rare, mother-of-pearl colored clouds caused by extreme weather conditions above Antarctica are a possible indication of global warming, Australian scientists said on Tuesday.

Known as nacreous clouds, the spectacular formations showing delicate wisps of colors were photographed in the sky over an Australian

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- Measures: Precision, recall, F_1, classification accuracy

Precision P and recall R

	in the class	not in the class
predicted to be in the class	true positives (TP)	false positives (FP)
predicted to not be in the class	false negatives (FN)	true negatives (TN)

TP, FP, FN, TN are counts of documents. The sum of these four counts is the total number of documents.

$$\begin{aligned} \text{precision:}P &= TP/(TP+FP) \\ \text{recall:}R &= TP/(TP+FN) \end{aligned}$$

A combined measure: F

- F_1 allows us to trade off precision against recall.

A combined measure: F

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- $$F_1 = \frac{1}{\frac{1}{2}\frac{1}{P} + \frac{1}{2}\frac{1}{R}} = \frac{2PR}{P+R}$$
- This is the harmonic mean of P and R: $\frac{1}{F} = \frac{1}{2}(\frac{1}{P} + \frac{1}{R})$

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  - Compute TP, FP, FN for each of the C classes

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  - Sum these C numbers (e.g., all TP to get aggregate TP)

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  - Compute TP, FP, FN for each of the C classes
  - Sum these C numbers (e.g., all TP to get aggregate TP)
  - Compute F_1 for aggregate TP, FP, FN

F_1 scores for Naive Bayes vs. other methods

(a)

	NB	Rocchio	kNN	SVM
micro-avg-L (90 classes)	80	85	86	89
macro-avg (90 classes)	47	59	60	60

(b)

	NB	Rocchio	kNN	trees	SVM
earn	96	93	97	98	98
acq	88	65	92	90	94
money-fx	57	47	78	66	75
grain	79	68	82	85	95
crude	80	70	86	85	89
trade	64	65	77	73	76
interest	65	63	74	67	78
ship	85	49	79	74	86
wheat	70	69	77	93	92
corn	65	48	78	92	90
micro-avg (top 10)	82	65	82	88	92
micro-avg-D (118 classes)	75	62	n/a	n/a	87

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Naive Bayes does pretty well, but some methods beat it consistently (e.g., SVM).

Take-away today

- Text classification: definition & relevance to information retrieval
- Naive Bayes: simple baseline text classifier
- Theory: derivation of Naive Bayes classification rule & analysis
- Evaluation of text classification: how do we know it worked / didn't work?

Resources

- Chapter 13 of IIR
- Resources at `http://cislmu.org`
  - Weka: A data mining software package that includes an implementation of Naive Bayes
  - Reuters-21578 – text classification evaluation set
  - Vulgarity classifier fail