# Introduction to Information Retrieval
http://informationretrieval.org

# IIR 13: Text Classification & Naive Bayes

Hinrich Schütze

Institute for Natural Language Processing, Universität Stuttgart

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# Overview

# Outline

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- The problem space relevance feedback belongs to is called classification.
- The notion of classification is very general and has many applications within and beyond information retrieval.

From information retrieval to text classification:

standing queries – Google Alerts

# Another TC task: 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 $\gamma$ that maps documents to classes:

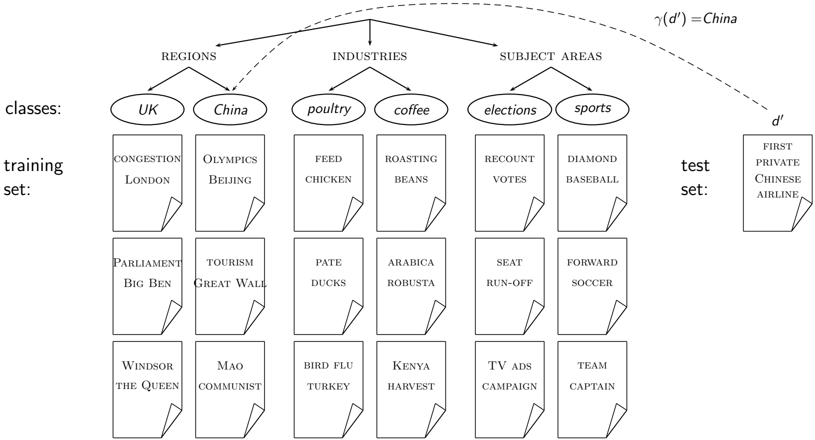
$$\gamma : \mathbb{X} \rightarrow \mathbb{C}$$

# Formal definition of TC: Application/Testing

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



Many search engine functionalities are based on classification.

Examples?

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- Machine-learned ranking function in ad hoc retrieval (relevant vs. nonrelevant)
- Semantic Web: Automatically add semantic tags for non-tagged text (e.g., for each paragraph: relevant to a vertical like health or not)

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- Consistent when the problem size and team is small
- Manual classification is difficult and expensive to scale.
- $\rightarrow$ We need automatic methods for classification.

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- Often: Boolean combinations (as in Google Alerts)
- Accuracy is very high if a rule has been carefully refined over time by a subject expert.
- Building and maintaining rule-based classification systems is expensive.

# A Verity topic (a complex classification rule)

```
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 PHRASE
                            *** 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
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                            # End of art topic
```

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- We will look at a couple of methods for doing this: Naive Bayes, Rocchio, kNN
- No free lunch: requires hand-classified training data
- But this manual classification can be done by non-experts.

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1. Text classification
2. Naive Bayes
3. Evaluation of TC
4. NB independence assumptions

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- We write $\hat{P}$ for $P$ since these values are estimates from the training set.

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- 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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- Questions?

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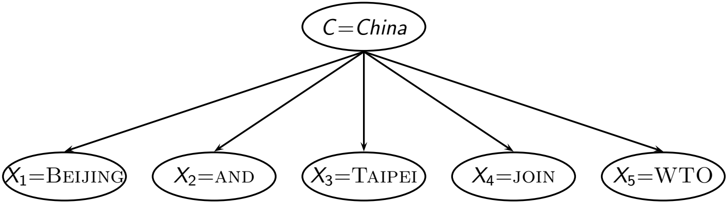
- We've made a Naive Bayes independence assumption here: $\hat{P}(t_{k_1}|c) = \hat{P}(t_{k_2}|c)$

# The problem with maximum likelihood estimates: Zeros




- In this example:

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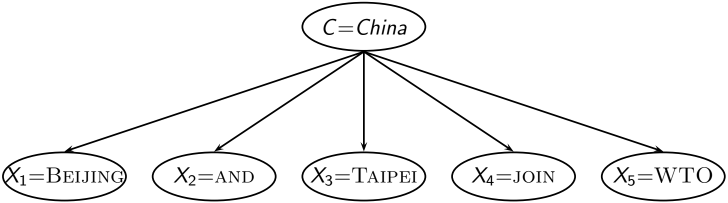


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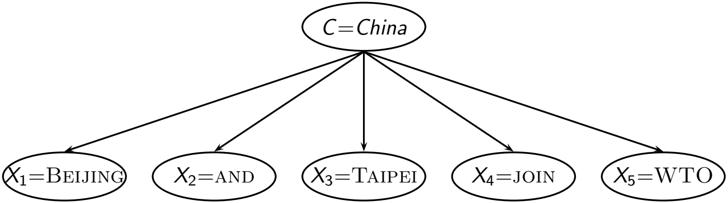


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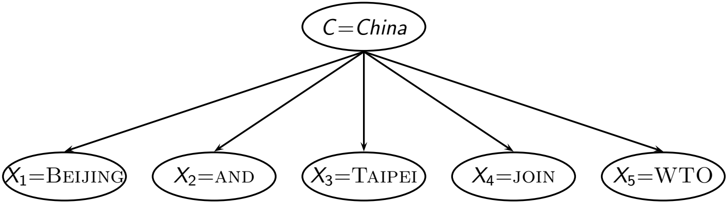


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- We will get $P(China|d) = 0$ for any document with WTO!
- Zero probabilities cannot be conditioned away.

# To avoid zeros: Add-one smoothing

- 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 different words (in this case 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
- Assign document to the class with the largest score

# Naive Bayes: Training

```
TrainMultinomialNB(C, D)
V ← ExtractVocabulary(D)
N ← CountDocs(D)
for each c ∈ C
do N_c ← CountDocsInClass(D, c)
    prior[c] ← N_c / N
    text_c ← ConcatenateTextOfAllDocsInClass(D, c)
    for each t ∈ V
    do T_ct ← CountTokensOfTerm(text_c, t)
    for each t ∈ V
    do condprob[t][c] ← (T_ct + 1) / Σ_t' (T_ct' + 1)
return V, prior, condprob
```

# Naive Bayes: Testing

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

$W \leftarrow$ ExtractTokensFromDoc($V$, $d$)
**for each** $c \in \mathbb{C}$
**do** $score[c] \leftarrow \log prior[c]$
  **for each** $t \in W$
  **do** $score[c] += \log condprob[t][c]$
**return** $\arg\max_{c \in \mathbb{C}} score[c]$

# Example: Data

| | 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 | ? |

# 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

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

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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|---|---|
| training | $\Theta(\lvert\mathbb{D}\rvert L_{\text{ave}} + \lvert\mathbb{C}\rvert\lvert V\rvert)$ |
| testing | $\Theta(L_{\text{a}} + \lvert\mathbb{C}\rvert M_{\text{a}}) = \Theta(\lvert\mathbb{C}\rvert M_{\text{a}})$ |

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- 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.

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- We will formally derive the classification rule . . .
- . . . and state the assumptions we make in that derivation explicitly.

# Derivation of Naive Bayes rule

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

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

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

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

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

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

# Too many parameters / sparseness

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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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- We would need a very, very large number of training examples to estimate that many parameters.
- This the problem of data sparseness.

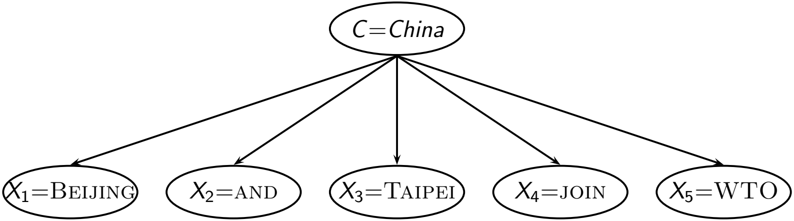
# Naive Bayes conditional independence assumption

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 priors and conditional probabilities: $\hat{P}(c) = \frac{N_c}{N}$ and $\hat{P}(t|c) = \frac{T_{ct}+1}{(\sum_{t' \in V} T_{ct'})+B}$

# Generative model

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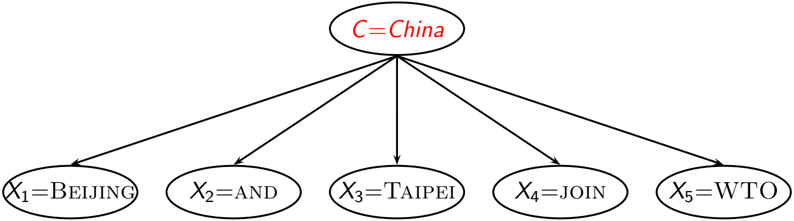


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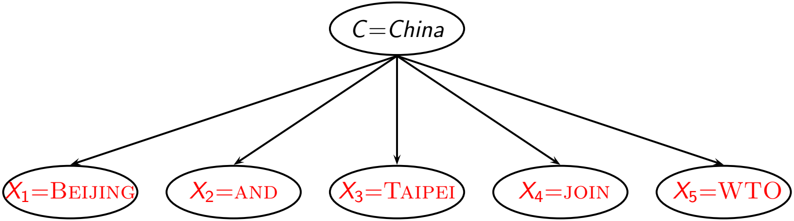


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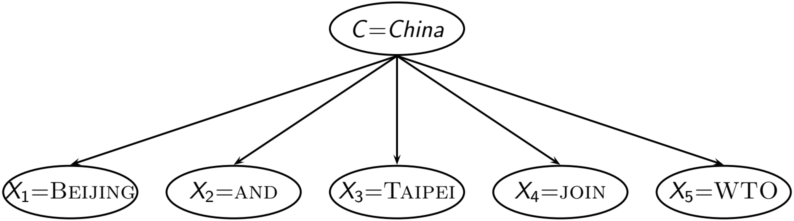


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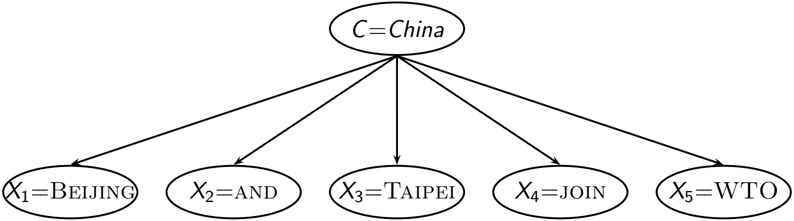


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- Questions?

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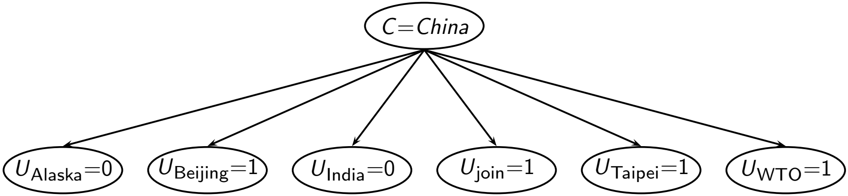
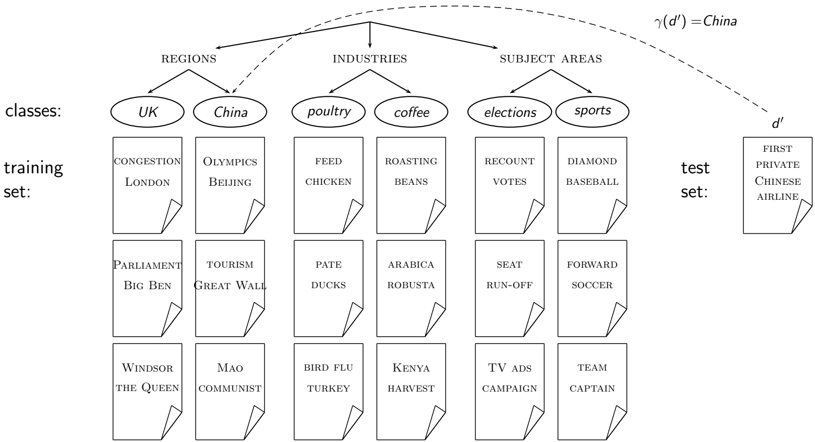
- $\hat{P}(t_{k_1}|c) = \hat{P}(t_{k_2}|c)$
- For example, for a document in the class *UK*, the probability of generating QUEEN in the first position of the document is the same as generating it in the last position.
- The two independence assumptions amount to the bag of words model.

# A different Naive Bayes model: Bernoulli model



# 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 |
| | avg. # bytes per word token (incl. spaces/punct.) | 6 |
| | avg. # bytes per word token (without spaces/punct.) | 4.5 |
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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

REUTERS

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## 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 meteorological base at Mawson Station on July 25.

# Evaluating classification

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- Measures: Precision, recall, $F_1$, classification accuracy

# 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).

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

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- A good dependable baseline for text classification (but not the best)

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- Reuters-21578 – the most famous text classification evaluation set (but now it's too small for realistic experiments)