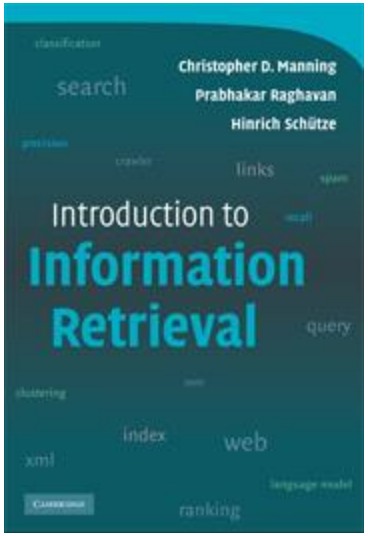
Information Retrieval and Organisation



Chapter 13

Text Classification and Naïve Bayes

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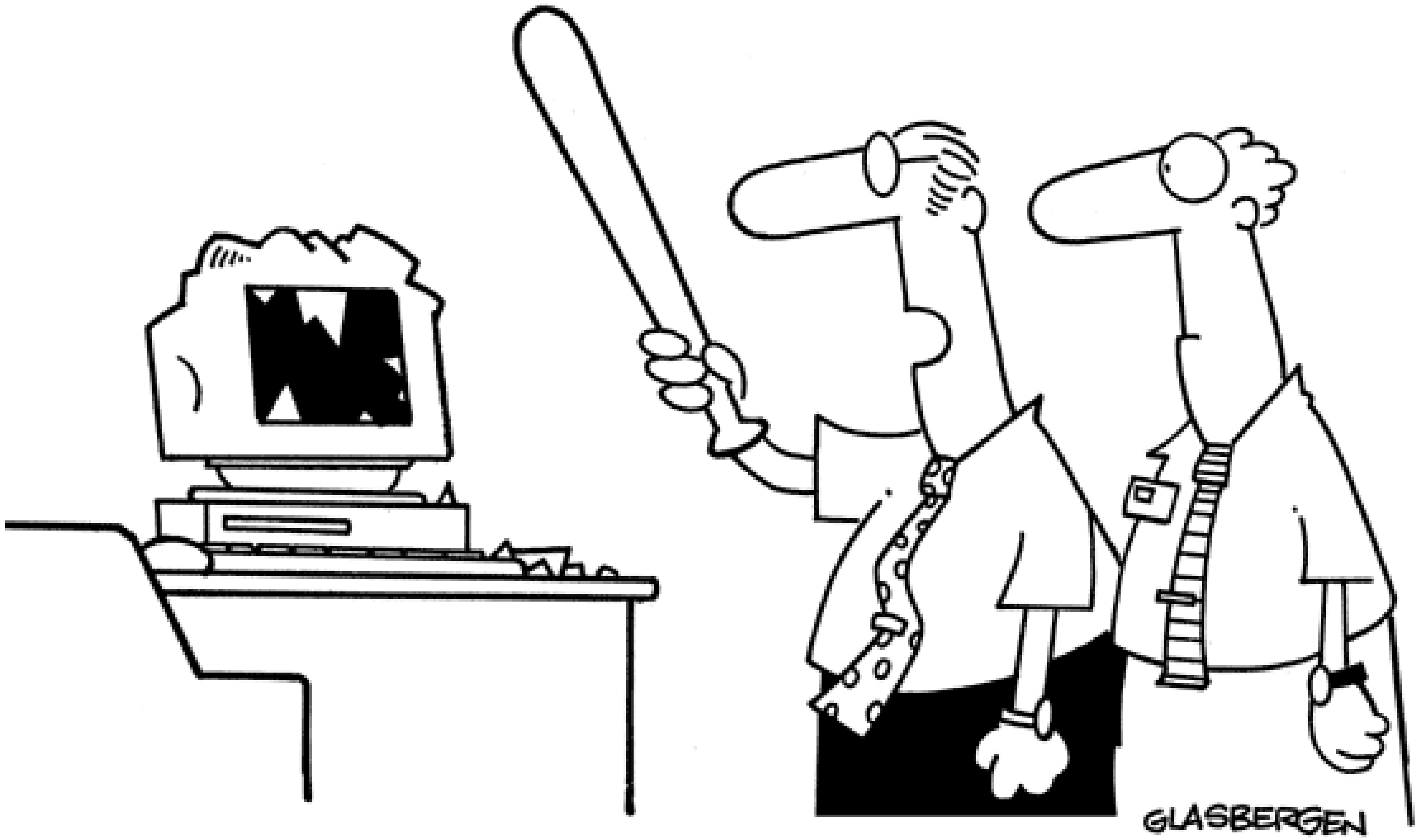
Motivation

- Relevance Feedback revisited
  - The user marks a number of documents as relevant/nonrelevant
  - We then try to use this information to return better search results.
  - Suppose we just tried to learn a filter for nonrelevant documents
  - This is an instance of a text classification problem:
    - Two “classes”: relevant, nonrelevant
    - For each document, decide whether it is relevant or nonrelevant

Motivation

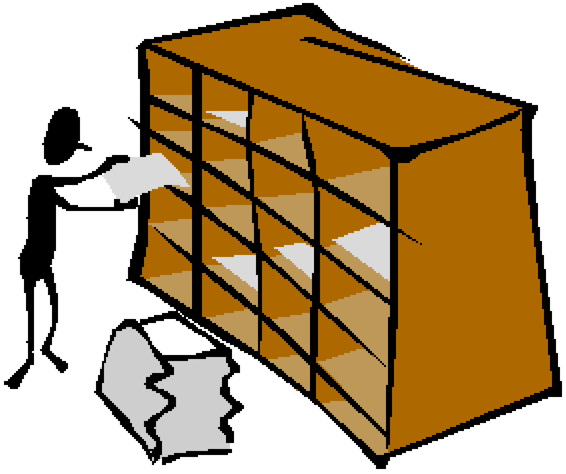
- The path from information retrieval to text classification:
  - You have an information need, say:
    - Unrest in the Niger delta region
  - You want to rerun an appropriate query periodically to find new news items on this topic
  - You will be sent new documents that are found
    - I.e., it's classification not ranking
- Such queries are called **standing queries**
  - Long used by "information professionals"
  - A modern mass instantiation is



"It's not the most sophisticated Spam blocker
I've tried, but it's the only one that works!"

Motivation

- Many search engine functionalities use classification
- The notion of classification is very general and has many applications within and beyond IR



Text Classification/Categorization

- Given:
  - A document, $d \in D$.
  - A set of classes $C = \{c_1, c_2, \ldots, c_n\}$.
- Determine:
  - The class of d: $c(d) \in C$, where $c(d)$ is a **classification function** ("classifier").

Text Classification Examples

- Classes are most often topics such as Yahoo-categories
  - e.g., “finance”, “sports”, “news>world>asia>business”
- Classes may be genres
  - e.g., “editorials”, “movie-reviews”, “news”
- Classes may be opinion on a person/product
  - e.g., “like”, “hate”, “neutral”

Text Classification Examples

- Classes may be domain-specific
  - e.g., “interesting-to-me” vs. “not-interesting-to-me”
  - e.g., “contains-adult-language” vs. “doesn’t”
  - e.g., English, French, Chinese, … (*language identification*)
  - e.g., “about-Linux” vs “not-about-Linux” (*vertical search*)
  - e.g., “link-spam” vs. “not-link-spam”

Classification Methods (1)

- Manual Classification
  - Used by
    - Yahoo! (originally; now present but downplayed), Looksmart, about.com, ODP, PubMed, …
  - Very accurate when job is done by experts
  - Consistent when the problem size and team is small
  - Difficult and expensive to scale
    - We need *automatic* classification methods for big problems.

Classification Methods (2)

- Hand-Coded Rules
  - Used by
    - CIA, Reuters, CS dept’s spam filter, …
    - Commercial systems for standing queries have complex query languages (everything in IR query languages plus accumulators)
  - Accuracy is often quite high, if the rules have been carefully refined over time by experts.
  - Expensive to build/maintain the rules.

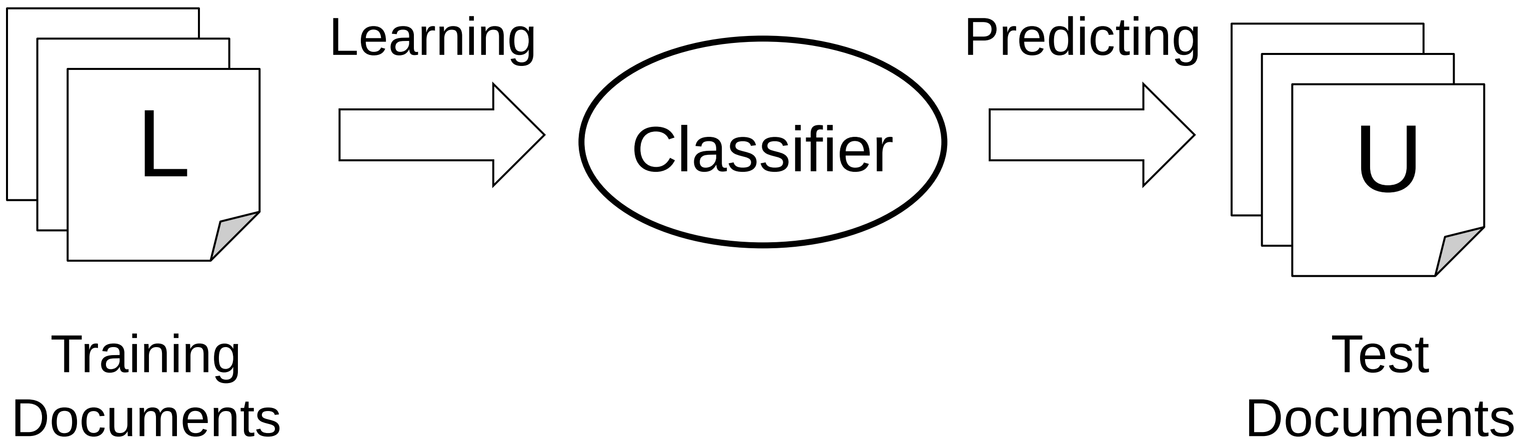
```
comment line                 # Beginning of art topic definition
top-level topic              art ACCRUE
                                 /author = "fsmith"
topic definition modifiers       /date   = "30-Dec-01"
                                 /annotation = "Topic created
                      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

- Companies (such as Verity) provide “IDE” for writing such complex classification rules
  - Hand-weighting of terms
  - Maintenance issues (author, etc.)

Classification Methods (3)

- (Supervised) Machine Learning
  - Used by
    - Google, Yahoo!, MSN, Autonomy, Verity, Enkata, …
    - Note that many commercial systems use a mixture of methods
  - There is no free lunch: hand-classified training data are required.
  - But the training data can be built up (and refined) easily by amateurs.
    - Such as graduate students ☺

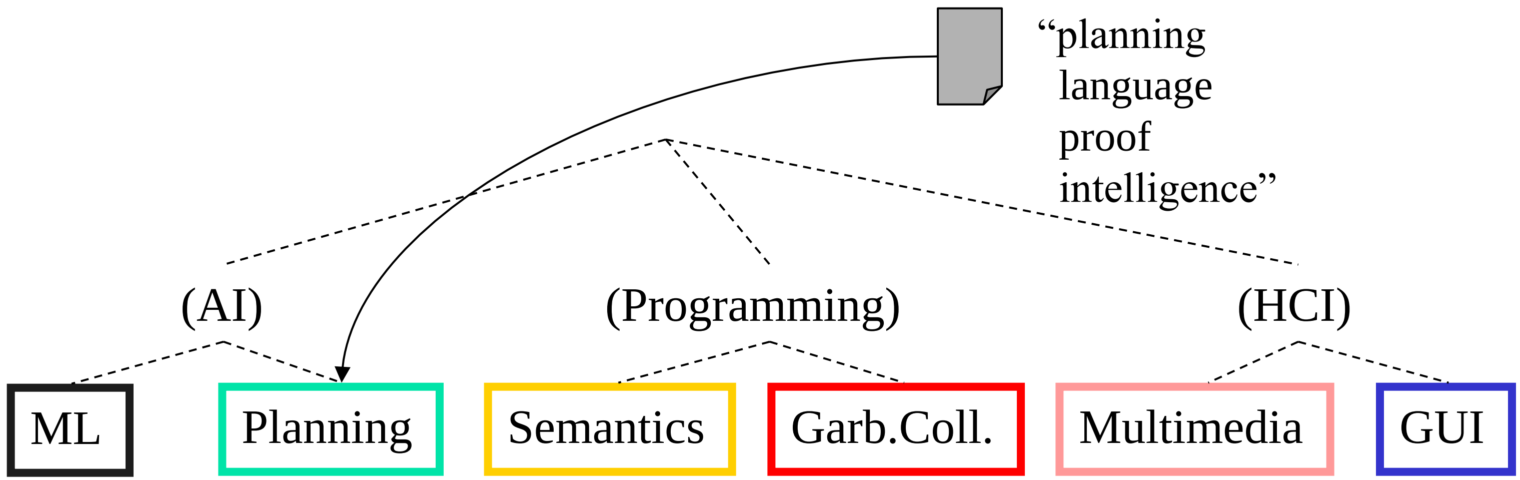
Text Classification via ML



Text Classification via ML

Test Data:

Classes:



Training Data:

learning	<u>planning</u>	programming	garbage	...	...
<u>intelligence</u>	temporal	semantics	collection		
algorithm	reasoning	<u>language</u>	memory		
reinforcement	plan	<u>proof</u>...	optimization		
network...	<u>language</u>...		region...		

(Note: in real life there is often a hierarchy, not present in the above problem statement; and also, you may get multi-topic papers for example on ML approaches to Garb. Coll.)

Evaluating Classification

- Classification Accuracy ($\#correct$ / $\#total$)
  - The proportion of correct predictions
  - Adequate if one class per document
- Precision, Recall ➔ F_1 measure (for each class)
  - Macro-averaging: computes performance measure for each class, and then computes a simple average over classes.
  - Micro-averaging: pools per-document predictions across classes, and then computes performance measure on the pooled contingency table.

Evaluating Classification

class 1	truth: yes	truth: no
call: yes	10	10
call: no	10	970

class 2	truth: yes	truth: no
call: yes	90	10
call: no	10	890

macro-averaged precision is $[10/(10 + 10) + 90/(10 + 90)]/2 = (0.5 + 0.9)/2 = 0.7$

pooled table	truth: yes	truth: no
call: yes	100	20
call: no	20	1860

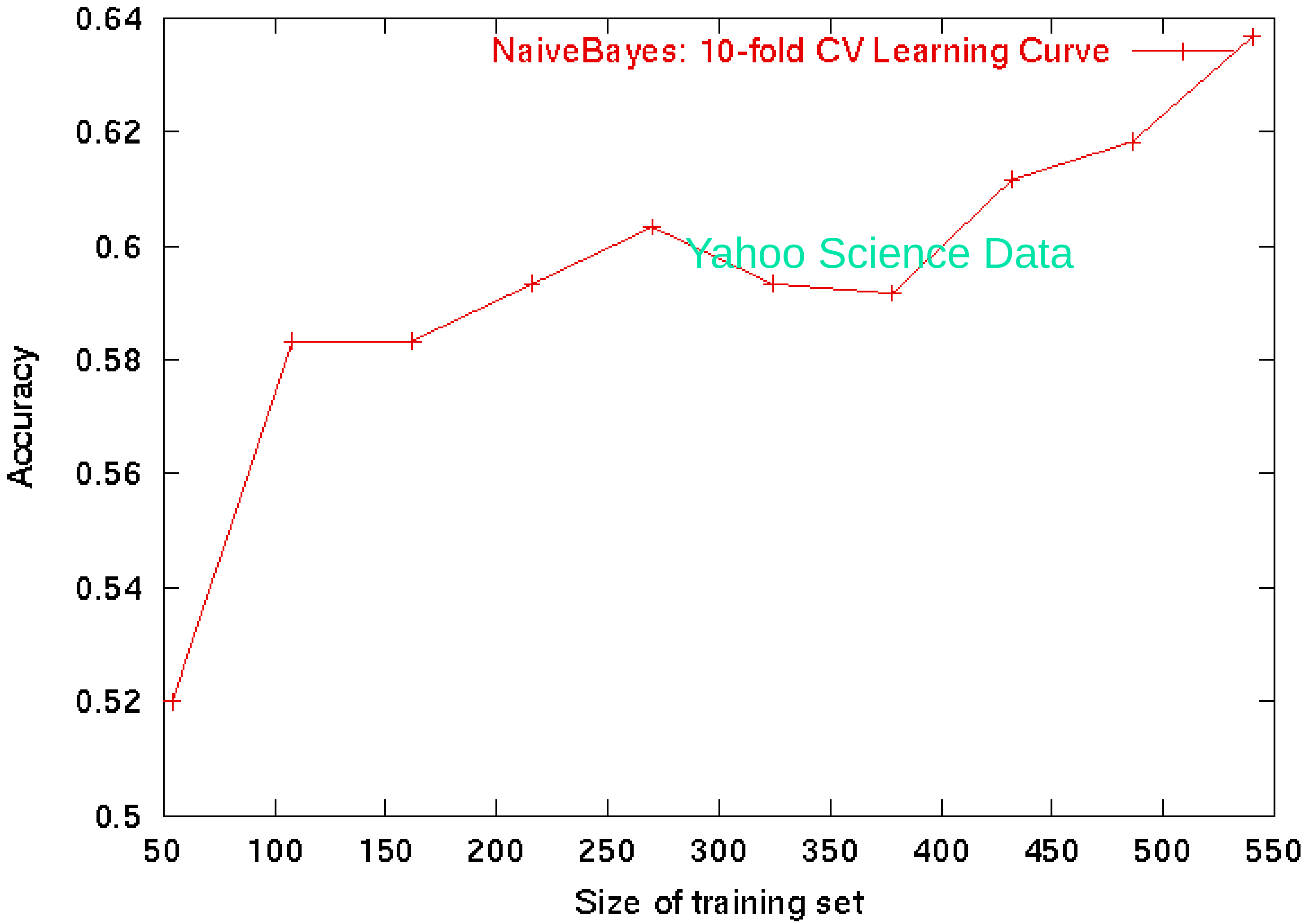
micro-averaged precision is $100/(100 + 20) \approx 0.83$

Evaluating Classification

- Evaluation must be done on test data that are independent of the training data (usually a disjoint set of instances).
- Results can vary based on sampling error due to different training and test sets.
- Average results over multiple training and test sets (splits of the overall data) for the best results.

Reuters-21578

Learning Curve



Naïve Bayes

- Before seeing the content of document d
  - Classify d to the class with maximum ***prior*** probability $P(c)$.
- After seeing the content of document d
  - Classify d to the class with maximum ***posteriori*** probability $P(c|d)$.
  - For each class $c_j \in C$, $P(c_j|d)$ can be estimated using the Bayes' Rule.

Naïve Bayes

- Bayes' Rule, Again!

$$P(c,d) = P(c \mid d)P(d) = P(d \mid c)P(c)$$

$$\Downarrow$$

$$\boxed{P(c \mid d) = \frac{P(d \mid c)P(c)}{P(d)}}$$

Naïve Bayes

$$c(d) = \operatorname*{argmax}_{c_j \in C} P(c_j \mid d)$$

$$= \operatorname*{argmax}_{c_j \in C} \frac{P(d \mid c_j) P(c_j)}{P(d)}$$

$$= \operatorname*{argmax}_{c_j \in C} P(d \mid c_j) P(c_j)$$

How can we estimate?

Naïve Bayes

- For each class $c_j \in C$, $P(c_j)$ can be estimated from the frequency of classes in the training data.

$$P(c_j) = \frac{N_j}{\sum_j N_j}$$

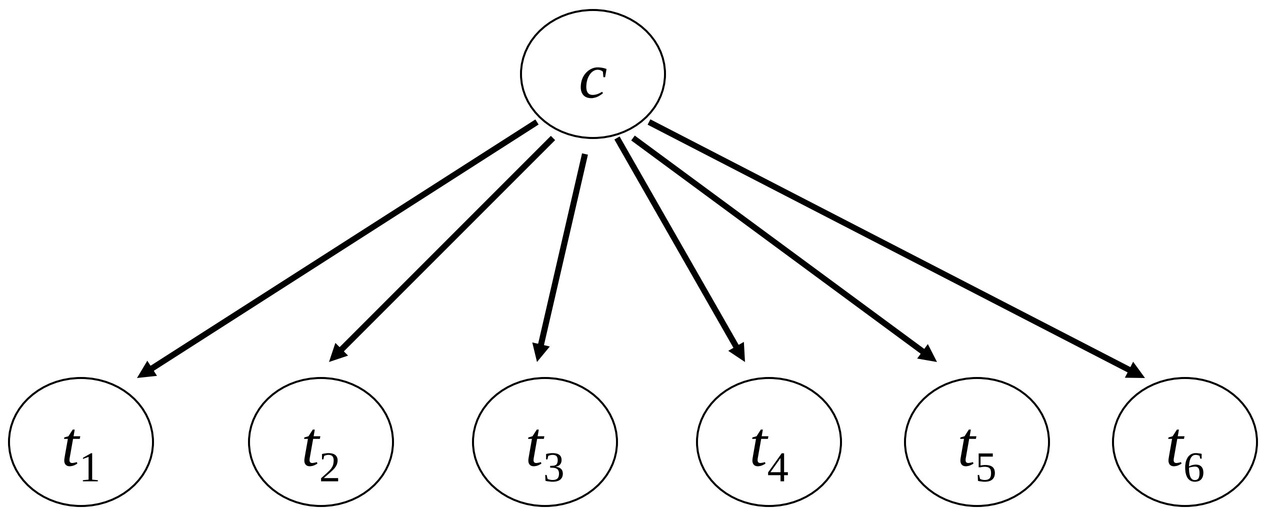
where N_j: the number of documents in the class c_j

Naïve Bayes

- $P(d|c_j) = P(t_1, t_2, \ldots, t_n|c_j)$
  - There are $O(|X|^n \bullet |C|)$ parameters.
  - Could only be estimated if a very, very large number of training examples was available.
- To facilitate the estimation of $P(d|c_j)$, two simplifying assumptions are made.
  - **Conditional Independence Assumption**
    - The term occurrences are independent of each other given the class.
  - **Positional Independence Assumption**
    - The conditional probabilities for a term are the same independent of position in the document.

Naïve Bayes

- Multinomial NB: effectively, the probability of each doc $P(d|c_j)$ is given by <u>a *class-specific* **unigram** language model</u>.



$$P(d \mid c_j) = \prod_{t_i \in d} P(t_i \mid c_j)$$

Smoothing for NB

- Why not just use MLE?
  - If a term t (in a test doc d) did not occur in the training data, $P(t|c_j)$ would be 0, and then $P(d|c_j)$ would be 0 no matter how strongly other terms in d are associated with class c_j.
- Add-One (Laplace) Smoothing

$$P(t_i \mid c_j) = \frac{T_{ji}}{\sum_i T_{ji}} \quad \Longrightarrow \quad \boxed{P(t_i \mid c_j) = \frac{(T_{ji} + 1)}{\sum_i (T_{ji} + 1)}}$$

T_{ji}: the number of occurrences of term i in documents of class c_j

Underflow Prevention

- Multiplying lots of probabilities, which are between 0 and 1 by definition, can result in floating-point underflow.
- Since $\log(xy) = \log(x) + \log(y)$, it is better to perform all computations by summing **logs** of probabilities rather than multiplying probabilities.
- Class with highest final un-normalized log probability score is still the most probable.

$$c_{NB} = \operatorname*{argmax}_{c_j \in C} \left\{ \log P(c_j) + \sum_{i \in positions} \log P(t_i \mid c_j) \right\}$$

Note that the model is now just max of sum of weights…

NB Algorithm: Training

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

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

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

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

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

    $prior[c] \leftarrow N_c/N$

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

    for each $t \in V$

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

    for each $t \in V$

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

return $V, prior, condprob$

NB Algorithm: Testing

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

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

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

do $score[c] \leftarrow \log prior[c]$

    for each $t \in W$

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

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

Time Complexity

- Training Time: $O(|D|L_d + |C||V|))$
  where L_d is the average length of a document in D.
  - Assumes V and all D_i , n_i, and n_{ij} pre-computed in $O(|D|L_d)$ time during one pass through all of the data.
  - Generally just $O(|D|L_d)$ since usually $|C||V| < |D|L_d$

Why?

- Testing Time: $O(|C|\ L_t)$
  where L_t is the average length of a test document.

Very efficient overall, linearly proportional to the time needed to just read in all the data.

Naïve Bayes is Not So Naïve

- Effectiveness
  - The Bayes *optimal* classifier if the independence assumptions do hold.
  - Often performs well even if the independence assumptions are badly violated.
  - Robust to irrelevant features.
  - Good in domains with many <u>equally important</u> features.
  - A good dependable baseline for text classification (though may not be the best).

Naïve Bayes is Not So Naïve

- Efficiency
  - Very fast
    - Linear training/testing time complexity
    - One pass of counting over the data
  - Low storage requirements.

Application: Web Page Cat.

- WebKB Experiment (1998)
  - Classify webpages from CS departments into:
    - student, faculty, course,project
  - Train on ~5,000 hand-labeled web pages
    - Cornell, Washington, U.Texas, Wisconsin
  - Crawl and classify a new site (CMU)

	Student	Faculty	Person	Project	Course	Departmt
Extracted	180	66	246	99	28	1
Correct	130	28	194	72	25	1
Accuracy:	72%	42%	79%	73%	89%	100%

Application: Email Filtering

- Naïve Bayes has found a home in spam filtering
  - Paul Graham's *A Plan for Spam*
    - A mutant with more mutant offspring ...
    - Naive Bayes-like classifier with weird parameter estimation
  - Widely used in spam filters
    - Classic Naive Bayes superior when appropriately used (According to David D. Lewis)
    - But also many other things: black hole lists, etc.
- Many email topic filters also use NB classifiers

SpamBayes

and Related

Application: Direct Marketing

- KDD-CUP 97 competition
  - Task: to predict if the recipient of mail will actually respond to the advertisement
    - Financial services industry
    - 750,000 records
  - Naïve Bayes: the 1st & 2nd place in among 16 (then) state-of-the-art algorithms.