Part 9: Text Classification; The Naïve Bayes algorithm

Francesco Ricci

Most of these slides comes from the course:

Information Retrieval and Web Search,

Christopher Manning and Prabhakar Raghavan

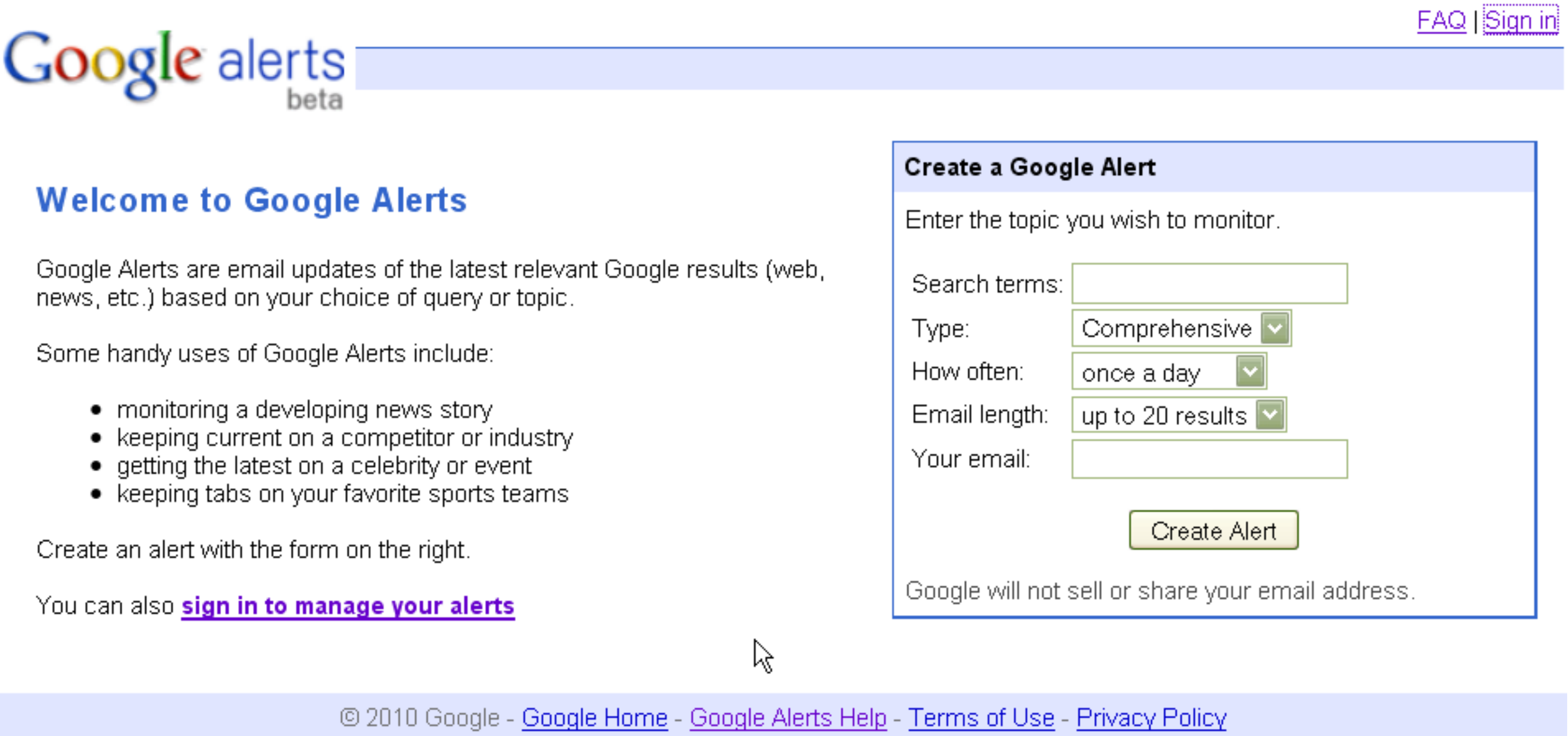
Content

- Introduction to Text Classification
- Bayes rule
- Naïve Bayes text classification
- Feature independence assumption
- Multivariate and Multinomial approaches
- Smoothing (avoid overfitting)
- Feature selection
  - Chi square and Mutual Information
- Evaluating NB classification.

Standing queries

- 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 **Google Alerts.**

Google alerts



Spam filtering: Another text classification task

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

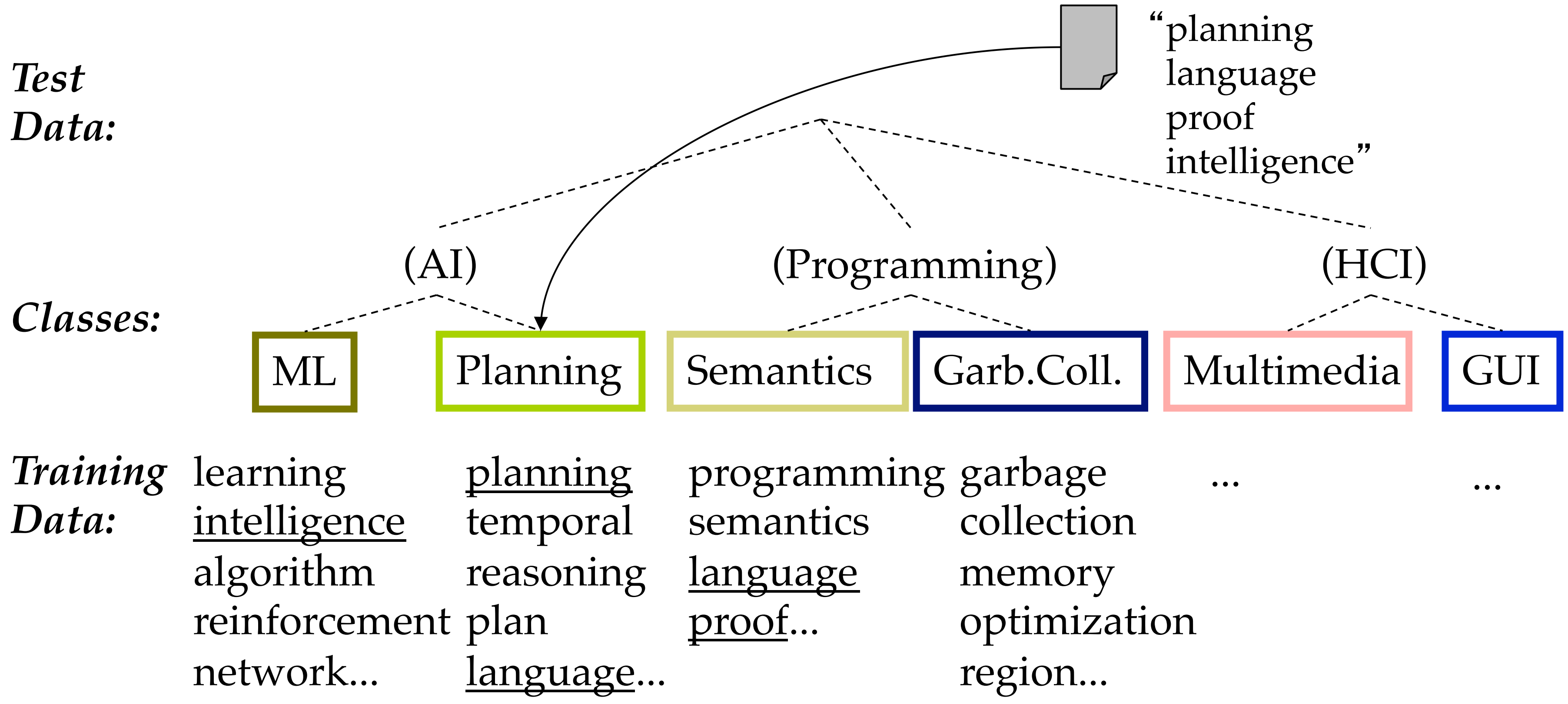
===

Categorization/Classification

- Given:
  - A **description of an instance**, $x \in X$, where X is the *instance language* or *instance space*
    - Issue: how to represent text documents – the representation determines what information is used for solving the classification task
  - A fixed **set of classes**:

    $C = \{c_1, c_2, \ldots, c_J\}$
- Determine:
  - The class of x: $c(x) \in C$, where $c(x)$ is a ***classification function*** whose domain is X and whose range is C
    - We want to know how to build classification functions ("classifiers").

Document Classification



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

More Text Classification Examples

- Many **search engine** functionalities use **classification**
- **Assign labels** to each **document** or web-page:
  - Labels are most often **topics** such as Yahoo-categories
    e.g., "finance," "sports," "news>world>asia>business"
  - Labels may be **genres**
    e.g., "editorials" "movie-reviews" "news“
  - Labels may be **opinion** on a person/product
    e.g., “like”, “hate”, “neutral”
  - Labels may be **domain-specific**
    e.g., "interesting-to-me" : "not-interesting-to-me”
    e.g., “contains adult language” : “doesn’t”
    e.g., language identification: English, French, Chinese, …
    e.g., “link spam” : “not link spam”
    e.g., "key-phrase" : "not key-phrase"

topics
genres
opinion
domain-specific

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**
    - Means we need automatic classification methods for big problems.

Classification Methods (2)

- **Hand-coded rule-based systems**
  - One technique used by CS dept's spam filter, Reuters, CIA, etc.
  - Companies (Verity) provide "IDE" for writing such rules
  - Example: *assign category if document contains a given Boolean combination of words*
  - **Standing queries:** Commercial systems have complex query languages (everything in IR query languages + accumulators)
  - Accuracy is often very high if a **rule has been carefully refined** over time by a subject expert
  - Building and maintaining these rules is expensive!

Verity topic (a classification rule)

comment line	`# Beginning of art topic definition`
top-level topic	`art ACCRUE`
topic definition modifiers	`/author = "fsmith"`
	`/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`
	`** 0.50 STEM`
	`/wordtext = vcr`
	`# End of art topic`

- Note:
  - maintenance issues (author, etc.)
  - Hand-weighting of terms
  - But it is easy to explain the results.

Classification Methods (3)

- **Supervised learning** of a document-label assignment function
- Many systems partly rely on machine learning (Autonomy, MSN, Verity, Enkata, Yahoo!, …)
  - k-Nearest Neighbors (simple, powerful)
  - Naive Bayes (simple, common method)
  - Support-vector machines (new, more powerful)
  - … plus many other methods
- No free lunch: **requires hand-classified training data**
- Note that many commercial systems use a mixture of methods.

Recall a few probability basics

- For events *a* and *b:*
- **Bayes' Rule**

$$p(a,b) = p(a \cap b) = p(a \mid b)p(b) = p(b \mid a)p(a)$$

$$\underbrace{p(a \mid b)}_{\text{Posterior}} = \frac{p(b \mid a)p(a)}{p(b)} = \frac{p(b \mid a)\overbrace{\boxed{p(a)}}^{\text{Prior}}}{\sum_{x=a,\bar{a}} p(b \mid x)p(x)}$$

- **Odds:**

$$O(a) = \frac{p(a)}{p(\bar{a})} = \frac{p(a)}{1 - p(a)}$$

Bayes' Rule Example

$$P(C,E) = P(C \mid E)P(E) = P(E \mid C)P(C)$$

$$P(C \mid E) = \frac{P(E \mid C)P(C)}{P(E)}$$

P(pass exam | attend classes) = ?

= P(pass exam) * P(attend classes | pass exam)/P(attend classes)

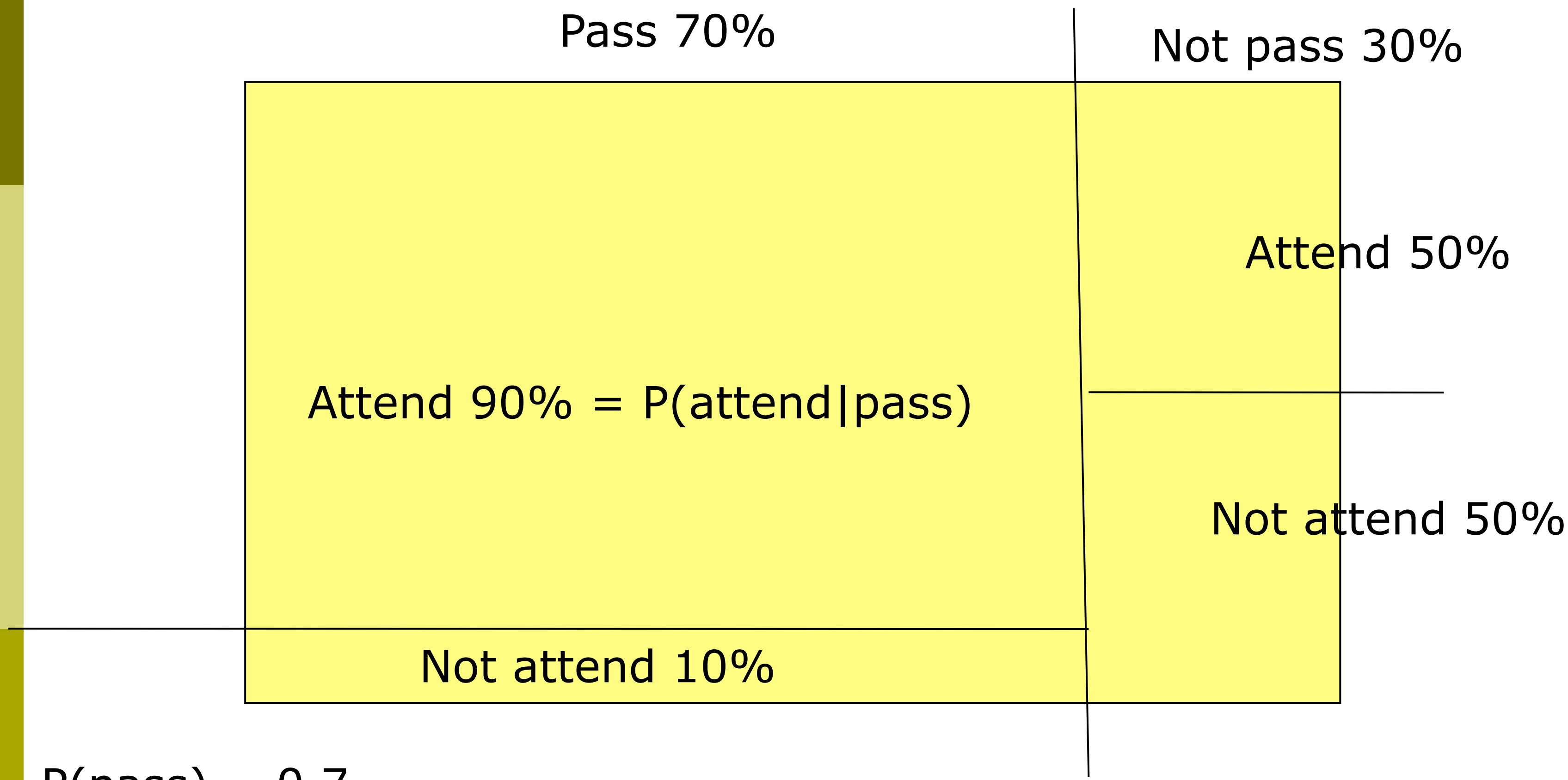
= 0.7 * 0.9/0.78

= 0.7 * 1.15 = 0.81

Initial estimation

Correction based on a ratio

Example explained



P(pass) = 0.7

P(attend) = P(attend| pass)P(pass) + P(attend | not pass)P(not pass)

= 0.9*0.7 + 0.5*0.3 = 0.63 + 0.15 = 0.78

p(pass | attend) = p(pass)*p(attend | pass)/p(attend)

= 0.7 * 0.9/0.78 = 0.81

Bayesian Methods

- Our focus this lecture
- Learning and classification methods based on **probability theory**
- **Bayes theorem** plays a critical role in probabilistic learning and classification
- Uses ***prior*** probability of each category given no information about an item
- Obtains a ***posterior*** **probability** distribution over the possible categories **given a description of an item**.

Naive Bayes Classifiers

- Task: Classify a new instance D based on a tuple of attribute values $D = \langle x_1, x_2, \ldots, x_n \rangle$ into one of the classes $c_j \in C$

$$c_{MAP} = \underset{c_j \in C}{\operatorname{argmax}} P(c_j \mid x_1, x_2, \ldots, x_n)$$

Maximum A Posteriori class

$$= \underset{c_j \in C}{\operatorname{argmax}} \frac{P(x_1, x_2, \ldots, x_n \mid c_j) P(c_j)}{P(x_1, x_2, \ldots, x_n)}$$

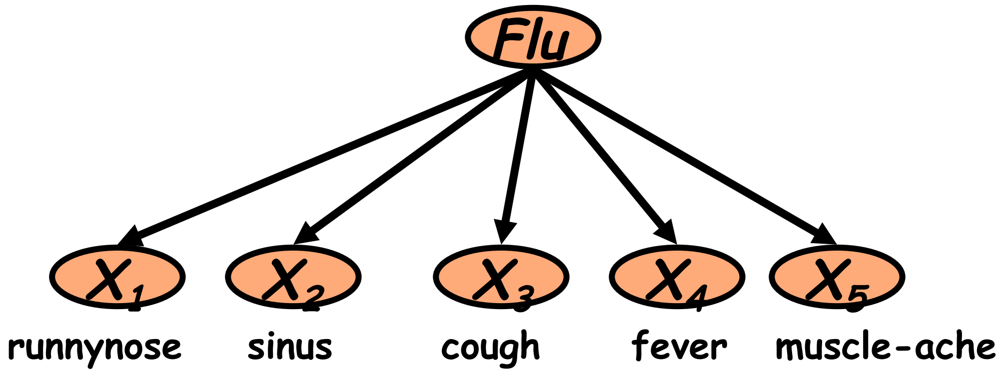
$$= \underset{c_j \in C}{\operatorname{argmax}} P(x_1, x_2, \ldots, x_n \mid c_j) P(c_j)$$

Naïve Bayes Assumption

- $P(c_j)$
  - Can be estimated from the frequency of classes in the training examples
- $P(x_1,x_2,\ldots,x_n|c_j)$
  - $O(|X|^n|C|)$ parameters (*assuming X finite*)
  - Could only be estimated if a very, very large number of training examples was available – or?
- Naïve Bayes Conditional Independence Assumption:
  - Assume that the probability of observing the **conjunction** of attributes is equal to the **product** of the individual probabilities $P(x_i|c_j)$.

$$c_{MAP} = \operatorname*{argmax}_{c_j \in C} P(c_j)\prod_{i=1}^{n} P(x_i \mid c_j)$$

The Naïve Bayes Classifier



- **Conditional Independence Assumption:** features detect term presence and are independent of each other given the class:

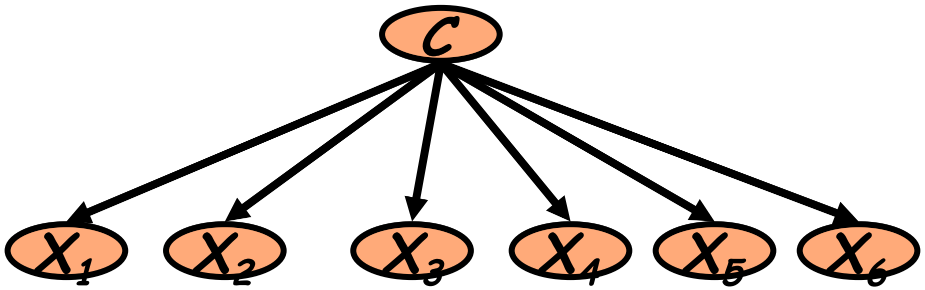
$$P(x_1,\ldots,x_5 \mid C) = P(x_1 \mid C) \bullet P(x_2 \mid C) \bullet \cdots \bullet P(x_5 \mid C)$$

- This model is appropriate for **binary** variables
  - Multivariate Bernoulli model

= many variables

=only 2 values – T or F

Learning the Model



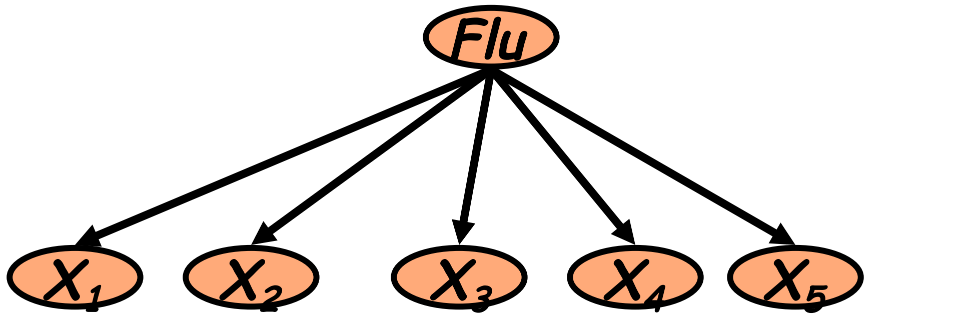
- First attempt: maximum likelihood estimates
  - simply use the frequencies in the data

$$\hat{P}(c_j) = \frac{N(C = c_j)}{N}$$

$$\hat{P}(x_i \mid c_j) = \frac{N(X_i = x_i, C = c_j)}{N(C = c_j)}$$

Estimated conditional probability that the attribute X_i (e.g. Fever) has the value x_i (True or False) – we will also write P(Fever | c_j) instead of P(Fever = T | c_j)

Problem with Max Likelihood



$$P(x_1,\ldots,x_5 \mid C) = P(x_1 \mid C) \bullet P(x_2 \mid C) \bullet \cdots \bullet P(x_5 \mid C)$$

- What if we have seen no training cases where patient had flu and muscle aches?

$$\hat{P}(X_5 = T \mid C = flu) = \frac{N(X_5 = T, C = flu)}{N(C = flu)} = 0$$

- Zero probabilities cannot be conditioned away, no matter the other evidence!

$$\ell = \arg\max_c \hat{P}(c) \prod_i \hat{P}(x_i \mid c)$$

Smoothing to Avoid Overfitting

$$\hat{P}(x_i \mid c_j) = \frac{N(X_i = x_i, C = c_j) + 1}{N(C = c_j) + k}$$

# of values of X_i

- Somewhat more subtle version

overall fraction in data where $X_i = x_i$

$$\hat{P}(x_i \mid c_j) = \frac{N(X_i = x_i, C = c_j) + mP(X_i = x_i)}{N(C = c_j) + m}$$

extent of "smoothing"

Example

	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	?

$$\begin{aligned}
\hat{P}(\text{Chinese}|c) &= (3+1)/(3+2) = 4/5 \\
\hat{P}(\text{Japan}|c) = \hat{P}(\text{Tokyo}|c) &= (0+1)/(3+2) = 1/5 \\
\hat{P}(\text{Beijing}|c) = \hat{P}(\text{Macao}|c) = \hat{P}(\text{Shanghai}|c) &= (1+1)/(3+2) = 2/5 \\
\hat{P}(\text{Chinese}|\overline{c}) &= (1+1)/(1+2) = 2/3 \\
\hat{P}(\text{Japan}|\overline{c}) = \hat{P}(\text{Tokyo}|\overline{c}) &= (1+1)/(1+2) = 2/3 \\
\hat{P}(\text{Beijing}|\overline{c}) = \hat{P}(\text{Macao}|\overline{c}) = \hat{P}(\text{Shanghai}|\overline{c}) &= (0+1)/(1+2) = 1/3
\end{aligned}$$

$$\begin{aligned}
\hat{P}(c|d_5) &\propto \hat{P}(c) \cdot \hat{P}(\text{Chinese}|c) \cdot \hat{P}(\text{Japan}|c) \cdot \hat{P}(\text{Tokyo}|c) \\
&\quad \cdot (1 - \hat{P}(\text{Beijing}|c)) \cdot (1 - \hat{P}(\text{Shanghai}|c)) \cdot (1 - \hat{P}(\text{Macao}|c)) \\
&= 3/4 \cdot 4/5 \cdot 1/5 \cdot 1/5 \cdot (1-2/5) \cdot (1-2/5) \cdot (1-2/5) \\
&\approx 0.005
\end{aligned}$$

Exercise

	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	?

$$
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\hat{P}(\text{Beijing}|\overline{c}) = \hat{P}(\text{Macao}|\overline{c}) = \hat{P}(\text{Shanghai}|\overline{c}) &= (0+1)/(1+2) = 1/3
\end{aligned}
$$

Estimate the probability that the test document does not belong to class c

Exercise

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\hat{P}(\text{Beijing}|\overline{c}) = \hat{P}(\text{Macao}|\overline{c}) = \hat{P}(\text{Shanghai}|\overline{c}) &= (0+1)/(1+2) = 1/3
\end{aligned}$$

$$\begin{aligned}
\hat{P}(\overline{c}|d_5) &\propto 1/4 \cdot 2/3 \cdot 2/3 \cdot 2/3 \cdot (1-1/3) \cdot (1-1/3) \cdot (1-1/3) \\
&\approx 0.022
\end{aligned}$$

<u>Multinomial</u> Naive Bayes Classifiers: Basic method

- Attributes (X_i) are text positions, values (x_i) are words:

$$c_{NB} = \underset{c_j \in C}{\operatorname{argmax}} P(c_j) \prod_{i=1}^{n} P(x_i \mid c_j)$$

$$= \underset{c_j \in C}{\operatorname{argmax}} P(c_j) P(X_1 = \text{"Our"} \mid c_j) \cdots P(X_n = \text{"text."} \mid c_j)$$

- Still too many possibilities
- Assume that classification is *independent* of the positions of the words

$$P(X_i = w \mid c) = P(X_j = w \mid c)$$

Multinomial Naïve Bayes: Learning

- From training corpus, extract *Vocabulary*
- Calculate required $P(c_j)$ and $P(x_k \mid c_j)$ terms
  - For each class c_j in C do
    - $docs_j \leftarrow$ subset of documents for which the target class is c_j

$$P(c_j) \leftarrow \frac{|docs_j|}{\text{total \# documents}}$$

  - $Text_j \leftarrow$ single document containing all $docs_j$
    - for each word x_k in *Vocabulary*
    - $n_{jk} \leftarrow$ number of occurrences of x_k in $Text_j$
    - $n_j \leftarrow$ number of words in $Text_j$

$$P(x_k \mid c_j) \leftarrow \frac{n_{jk} + \alpha}{n_j + \alpha\,|Vocabulary|}$$

Assume is = 1; this is for smoothing

Multinomial Naïve Bayes: Classifying

- $\text{positions} \leftarrow$ all word positions in **current document** which contain tokens found in $\mathit{Vocabulary}$
- Return c_{NB} such that:

$$c_{NB} = \underset{c_j \in C}{\operatorname{argmax}} P(c_j) \prod_{i \in positions} P(x_i \mid c_j)$$

Example

	docID	words in document	in $c = China$?
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test set	5	Chinese Chinese Chinese Tokyo Japan	?

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

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

Naive Bayes: Time Complexity

- Training Time: if L_d is the average length of a document in D
  - $O(|D|L_d + |C||V|))$

Number of conditional probabilities to estimate

Scan the documents to compute the vocabulary and the frequencies of words

  - Assumes that V and all $docs_j$, n_j, and n_{jk} are computed in $O(|D|L_d)$ time during one pass through all of the data
  - Generally just $O(|D|L_d)$ since usually $|C||V| < |D|L_d$
- Test 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.

Underflow Prevention: log space

- 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

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

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

Sounds familiar?

Summary - Two Models: Multivariate Bernoulli

- One feature X_w for each word in dictionary
- X_w = true in document d if w appears in d
- **Naive Bayes assumption:**
  - Given the document's topic (class), appearance of one word in the document tells us nothing about chances that another word appears (independence)

Summary - Two Models: Multinomial

- One feature X_i for each word positions in document
  - feature's values are all words in dictionary
- Value of X_i is the word in position i
- **Naïve Bayes assumption:**
  - Given the document's topic (class), word in one position in the document tells us nothing about words in other positions
- **Second assumption:**
  - Word appearance does not depend on position - for all positions *i,j*, word *w*, and class *c*

$$P(X_i = w \mid c) = P(X_j = w \mid c)$$

  - Just have one multinomial feature predicting all words.

Parameter estimation

- **Multivariate Bernoulli model:**

$$\hat{P}(X_w = true \mid c_j) = \boxed{\text{fraction of documents of topic } c_j \text{ in which word } w \text{ appears}}$$

- **Multinomial model:**

$$\hat{P}(X_i = w \mid c_j) = \boxed{\text{fraction of times in which word } w \text{ appears across all documents of topic } c_j}$$

  - Can create a mega-document for topic *j* by concatenating all documents in this topic
  - Use frequency of *w* in mega-document.

Classification

- Multinomial vs Multivariate Bernoulli?
- **Multinomial** model is almost always **more effective** in text applications!
  - See results figures later
- See *IIR* sections 13.2 and 13.3 for worked examples with each model

Feature Selection: Why?

- Text collections have a large number of features
  - 10,000 – 1,000,000 unique words … and more
- May make using a particular classifier unfeasible
  - Some classifiers can’t deal with 100,000 of features
- Reduces training time
  - Training time for some methods is quadratic or worse in the number of features
- Can improve generalization (performance)
  - Eliminates noise features
  - Avoids overfitting.

Feature selection: how?

- Two ideas:
  - **Hypothesis testing statistics:**
    - Are we confident that the value of one categorical variable is associated with the value of another
    - *Chi-square test* (http://faculty.vassar.edu/lowry/webtext.html chapter 8)
  - **Information theory:**
    - How much information does the value of one categorical variable give you about the value of another
    - *Mutual information*

χ^2 statistic (CHI) – testing independence of class and term

	Term = jaguar	*Term ≠ jaguar*
Class = auto	2	500
Class ≠ auto	3	9500

- If the term "jaguar" is **independent** from the class "auto" we should have:
- P(C(d)=auto, d contains jaguar) = P(C(d)= auto) * P(d contains jaguar)
- 2/10005=? 502/10005 * 5/10005
- 0.00019 =? 0.0501 * 0.00049 = 0.000025 NOT REALLY!
- To be independent we should have more documents that contains jaguar but are not in class auto (38).

χ^2 statistic (CHI)

- χ2 is interested in $(f_o - f_e)^2/f_e$ summed over all table entries: is the observed number what you'd expect given the marginals?

$$\chi^2(j,a) = \sum (O-E)^2/E = (2-.25)^2/.25 + (3-4.75)^2/4.75$$
$$+ (500-502)^2/502 + (9500-9498)^2/9498 = 12.9\ (p < .001)$$

- The null hypothesis (the two variables are independent) is rejected with confidence .999,
- since 12.9 > 10.83 (the critical value for .999 confidence for a 1 degree of freedom χ2 distribution).

	Term = jaguar	*Term ≠ jaguar*
Class = auto	2 *(0.25)*	500 *(502)*
Class ≠ auto	3 *(4.75)*	9500 *(9498)*

expected: f_e

observed: f_o

Expected value, for instance in the up-left cell is: P(c=auto)*P(T=jaguar)* #of cases = 502/10005 * 5/10005 * 10005 = 0.2508

χ2 statistic (CHI)

There is a "simpler" formula for 2x2 χ^2:

$$\chi^2(t,c) = \frac{N \times (AD - CB)^2}{(A+C) \times (B+D) \times (A+B) \times (C+D)}$$

A = #(t,c)	C = #(¬t,c)
B = #(t,¬c)	D = #(¬t, ¬c)

$N = A + B + C + D$

Feature selection via Mutual Information

- In training set, choose *k* words which give most info on the knowledge of the categories
- The **Mutual Information** between a word, class is:

$$I(U,C) = \sum_{e_w \in \{0,1\}} \sum_{e_c \in \{0,1\}} p(U = e_w, C = e_c) \log \frac{p(U = e_w, C = e_c)}{p(U = e_w) p(C = e_c)}$$

- U=1 (U=0) means the document (does not) contains w
- C=1 (C=0) the document is (not) in class c
- For each word *w* and each category *c*
- *I(X,Y) = H(X) – H(X|Y)*
  $= -\Sigma_i\ p(x_i) \log p(x_i) + \Sigma_i\ p(y_j)\ H(X|Y=y_j)$
- *H is called the Entropy*

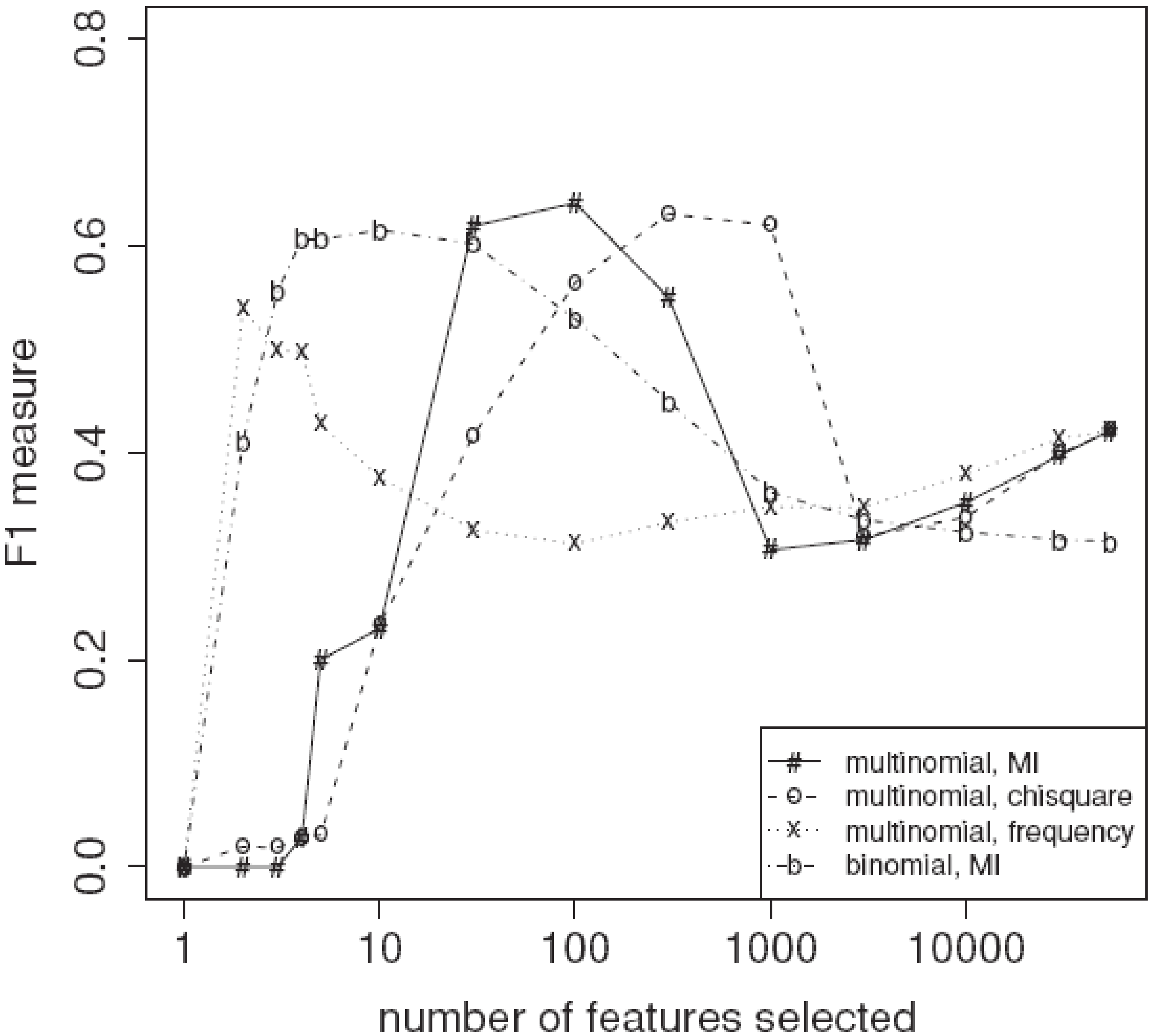
Feature selection via MI (contd.)

- For each category we build a list of *k* most discriminating terms
- For example (on 20 Newsgroups):
  - ***sci.electronics:*** circuit, voltage, amp, ground, copy, battery, electronics, cooling, …
  - ***rec.autos:*** car, cars, engine, ford, dealer, mustang, oil, collision, autos, tires, toyota, …
- Greedy: does not account for correlations between terms
- Why?

Feature Selection

- Mutual Information
  - Clear information-theoretic interpretation
  - May select very slightly informative **frequent** terms that are not very useful for classification
- Chi-square
  - Statistical foundation
  - May select **rare statistically correlated** but uninformative terms
- Just use the commonest terms?
  - No particular foundation
  - In practice, this is often 90% as good.

Example



F1 measure
0.0
0.2
0.4
0.6
0.8
1
10
100
1000
10000
number of features selected
multinomial, MI
multinomial, chisquare
multinomial, frequency
binomial, MI

Feature selection for NB

- In general feature selection is *necessary* for **multivariate Bernoulli** NB
- Otherwise you suffer from noise, multi-counting

- "Feature selection" really means something different for multinomial NB - it means **dictionary truncation**
  - The multinomial NB model only has 1 feature
- This "feature selection" normally isn't needed for multinomial NB, but may help a fraction with quantities that are badly estimated.

Evaluating Categorization

- Evaluation must be done on **test data** that are **independent** of the **training data** (usually a disjoint set of instances).
- *Classification accuracy*: c/n where n is the total number of test instances and c is the number of test instances correctly classified by the system
  - Adequate if one class per document (*and positive and negative examples have similar cardinalities*)
  - Otherwise **F measure** for each class
- 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.

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)

- Results:

	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%

Actually this is not accuracy but …

Most relevant features: MI

Faculty

associate	0.00417
chair	0.00303
member	0.00288
ph	0.00287
director	0.00282
fax	0.00279
journal	0.00271
recent	0.00260
received	0.00258
award	0.00250

Students

resume	0.00516
advisor	0.00456
student	0.00387
working	0.00361
stuff	0.00359
links	0.00355
homepage	0.00345
interests	0.00332
personal	0.00332
favorite	0.00310

Courses

homework	0.00413
syllabus	0.00399
assignments	0.00388
exam	0.00385
grading	0.00381
midterm	0.00374
pm	0.00371
instructor	0.00370
due	0.00364
final	0.00355

Departments

departmental	0.01246
colloquia	0.01076
epartment	0.01045
seminars	0.00997
schedules	0.00879
webmaster	0.00879
events	0.00826
facilities	0.00807
eople	0.00772
postgraduate	0.00764

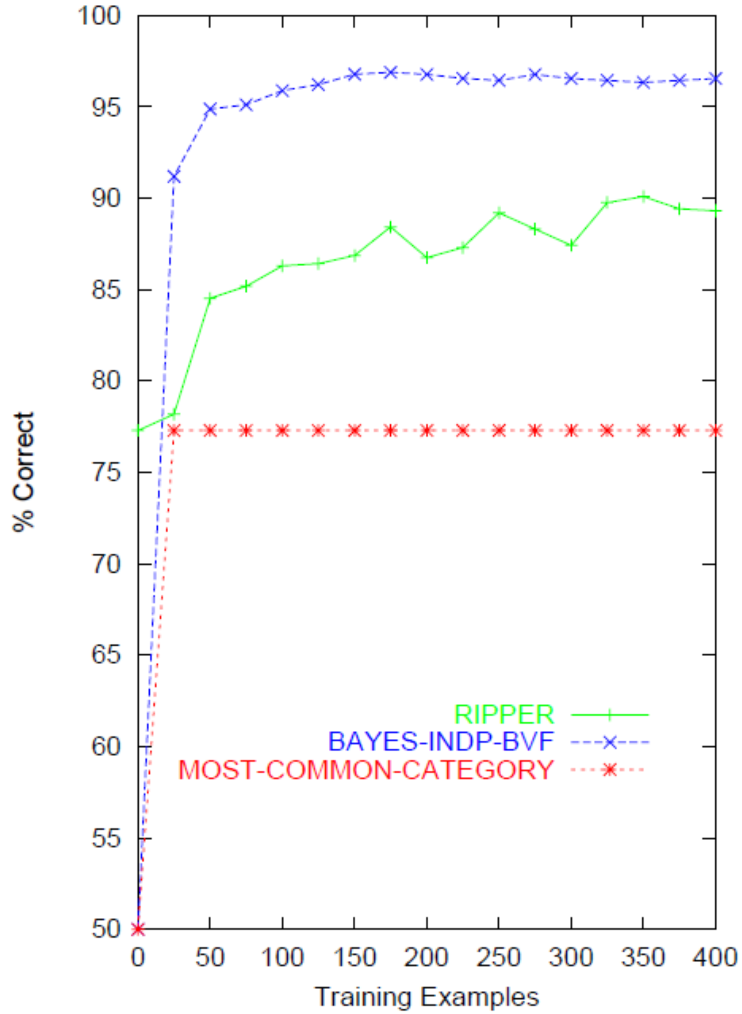
Research Projects

investigators	0.00256
group	0.00250
members	0.00242
researchers	0.00241
laboratory	0.00238
develop	0.00201
related	0.00200
arpa	0.00187
affiliated	0.00184
project	0.00183

Others

type	0.00164
jan	0.00148
enter	0.00145
random	0.00142
program	0.00136
net	0.00128
time	0.00128
format	0.00124
access	0.00117
begin	0.00116

Naïve Bayes on spam email



Naïve Bayes Posterior Probabilities

- **Classification results** of naïve Bayes (the class with maximum posterior probability) **are usually fairly accurate**
- However, due to the inadequacy of the conditional independence assumption, the **actual posterior-probability numerical estimates are not**
  - Output probabilities are commonly very close to 0 or 1
- Correct estimation $\Rightarrow$ accurate prediction, but correct probability estimation is NOT necessary for accurate prediction (just need right ordering of probabilities).

Naive Bayes is Not So Naive

- Naïve Bayes: First and Second place in KDD-CUP 97 competition, among 16 (then) state of the art algorithms

  Goal: Financial services industry direct mail response prediction model: Predict if the recipient of mail will actually respond to the advertisement – 750,000 records.
- Robust to Irrelevant Features

  Irrelevant Features cancel each other without affecting results

  Instead Decision Trees can heavily suffer from this.
- Very good in domains with many equally important features

  Decision Trees suffer from *fragmentation* in such cases – especially if little data
- A good dependable baseline for text classification (but not the best)!
- Optimal if the Independence Assumptions hold: If assumed independence is correct, then it is the Bayes Optimal Classifier for problem
- Very Fast: Learning with one pass of counting over the data; testing linear in the number of attributes, and document collection size
- Low Storage requirements

Resources

- IIR 13
- Tom Mitchell, Machine Learning. McGraw-Hill, 1997.
  - Clear simple explanation of Naïve Bayes