Introduction to

Information Retrieval

CS276: Information Retrieval and Web Search
Christopher Manning and Prabhakar Raghavan

Lecture 10: Text Classification;
The Naive Bayes algorithm
Relevance feedback revisited

- In relevance feedback, the user marks a few documents as relevant/nonrelevant
- The choices can be viewed as classes or categories
- For several documents, the user decides which of these two classes is correct
- The IR system then uses these judgments to build a better model of the information need
- So, relevance feedback can be viewed as a form of text classification (deciding between several classes)
- The notion of classification is very general and has many applications within and beyond IR
Standing queries

- The path from IR to text classification:
  - You have an information need to monitor, 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 text classification not ranking
- Such queries are called **standing queries**
  - Long used by “information professionals”
  - A modern mass instantiation is **Google Alerts**
- Standing queries are (hand-written) text classifiers
Spam filtering: Another text classification task

From: "" <takworlId@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
=================================================================

4
Text classification

- Today:
  - Introduction to Text Classification
    - Also widely known as “text categorization”. Same thing.
  - Naïve Bayes text classification
    - Including a little on Probabilistic Language Models
Categorization/Classification

- Given:
  - A description of an instance, \( d \in X \)
    - \( X \) is the instance language or instance space.
    - Issue: how to represent text documents.
    - Usually some type of high-dimensional space
  - A fixed set of classes:
    \( C = \{c_1, c_2, \ldots, c_J\} \)

- Determine:
  - The category of \( d \): \( \gamma(d) \in C \), where \( \gamma(d) \) is a classification function whose domain is \( X \) and whose range is \( C \).
    - We want to know how to build classification functions (“classifiers”).
Supervised Classification

- Given:
  - A description of an instance, \( d \in X \)
    - \( X \) is the *instance language* or *instance space*.
  - A fixed set of classes:
    - \( C = \{ c_1, c_2, \ldots, c_j \} \)
  - A training set \( D \) of labeled documents with each labeled document \( \langle d, c \rangle \in X \times C \)

- Determine:
  - A learning method or algorithm which will enable us to learn a classifier \( \gamma : X \rightarrow C \)
  - For a test document \( d \), we assign it the class \( \gamma(d) \in C \)
Document Classification

**Test Data:**

```
(AI) Planning (Programming) (HCI)
```

**Classes:**

```
ML Planning Semantics Garb.Coll. Multimedia GUI
```

**Training Data:**

```
learning intelligence algorithm reinforcement network...
```

(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

- Assigning labels to documents or web-pages:
  - Labels are most often topics such as Yahoo-categories
    - "finance," "sports," "news>world>asia>business"
  - Labels may be genres
    - "editorials" "movie-reviews" "news"
  - Labels may be opinion on a person/product
    - “like”, “hate”, “neutral”
  - Labels may be domain-specific
    - "interesting-to-me" : "not-interesting-to-me"
    - “contains adult language” : “doesn’t”
    - language identification: English, French, Chinese, ...
    - search vertical: about Linux versus not
    - “link spam” : “not link spam”
Classification Methods (1)

- Manual classification
  - Used by the original Yahoo! Directory
  - 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)

- Automatic document classification
  - Hand-coded rule-based systems
    - One technique used by CS dept’s spam filter, Reuters, CIA, etc.
    - It’s what Google Alerts is doing
      - Widely deployed in government and enterprise
    - Companies provide “IDE” for writing such rules
    - E.g., assign category if document contains a given boolean combination of words
    - Standing queries: Commercial systems have complex query languages (everything in IR query languages + score 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
A Verity topic
A complex classification rule

- Note:
  - maintenance issues (author, etc.)
  - Hand-weighting of terms

[Verity was bought by Autonomy.]
Classification Methods (3)

- Supervised learning of a document-label assignment function
  - Many systems partly rely on machine learning (Autonomy, Microsoft, 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
  - But data can be built up (and refined) by amateurs

- Many commercial systems use a mixture of methods
Probabilistic relevance feedback

- Rather than reweighting in a vector space...
- If user has told us some relevant and some irrelevant documents, then we can proceed to build a probabilistic classifier,
  - such as the Naive Bayes model we will look at today:
    - $P(t_k | R) = \frac{|D_{rk}|}{|D_r|}$
    - $P(t_k | NR) = \frac{|D_{nrk}|}{|D_{nr}|}$
  - $t_k$ is a term; $D_r$ is the set of known relevant documents; $D_{rk}$ is the subset that contain $t_k$; $D_{nr}$ is the set of known irrelevant documents; $D_{nrk}$ is the subset that contain $t_k$. 
Recall a few probability basics

- For events $a$ and $b$:
- Bayes’ Rule

\[
p(a, b) = p(a \cap b) = p(a \mid b) p(b) = p(b \mid a) p(a)
\]

\[
p(\overline{a} \mid b) p(b) = p(b \mid \overline{a}) p(\overline{a})
\]

\[
p(a \mid b) = \frac{p(b \mid a) p(a)}{p(b)} = \frac{p(b \mid a) p(a)}{\sum_{x=a,\overline{a}} p(b \mid x) p(x)}
\]

- Odds:

\[
O(a) = \frac{p(a)}{p(\overline{a})} = \frac{p(a)}{1 - p(a)}
\]
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.
- Builds a *generative model* that approximates how data is produced
- Uses *prior* probability of each category given no information about an item.
- Categorization produces a *posterior* probability distribution over the possible categories given a description of an item.
Bayes’ Rule for text classification

- For a document $d$ and a class $c$

\[
P(c, d) = P(c \mid d)P(d) = P(d \mid c)P(c)
\]

\[
P(c \mid d) = \frac{P(d \mid c)P(c)}{P(d)}
\]
Naive Bayes Classifiers

Task: Classify a new instance $d$ based on a tuple of attribute values into one of the classes $c_j \in C$

$$d = \langle x_1, x_2, \ldots, x_n \rangle$$

$$c_{MAP} = \arg\max_{c_j \in C} P(c_j \mid x_1, x_2, \ldots, x_n)$$

$$= \arg\max_{c_j \in C} \frac{P(x_1, x_2, \ldots, x_n \mid c_j)P(c_j)}{P(x_1, x_2, \ldots, x_n)}$$

$$= \arg\max_{c_j \in C} P(x_1, x_2, \ldots, x_n \mid c_j)P(c_j)$$

MAP is “maximum a posteriori” = most likely class
Naïve Bayes Classifier: Naïve Bayes Assumption

- $P(c_j)$
  - Can be estimated from the frequency of classes in the training examples.

- $P(x_1, x_2, ..., x_n | c_j)$
  - $O(|X|^n \cdot |C|)$ parameters
  - Could only be estimated if a very, very large number of training examples was available.

Naïve Bayes Conditional Independence Assumption:

- Assume that the probability of observing the conjunction of attributes is equal to the product of the individual probabilities $P(x_i | c_j)$. 
The Naïve Bayes Classifier

- **Conditional Independence Assumption:**
  features detect term presence and are independent of each other given the class:
  \[ P(X_1, \ldots, X_5 \mid C) = P(X_1 \mid C) \cdot P(X_2 \mid C) \cdot \cdots \cdot P(X_5 \mid C) \]

- This model is appropriate for binary variables
  - Multivariate Bernoulli model
Learning the Model

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

\[
P(c_j) = \frac{N(C = c_j)}{N}
\]

\[
P(x_i | c_j) = \frac{N(X_i = x_i, C = c_j)}{N(C = c_j)}
\]
Problem with Maximum Likelihood

\[ P(X_1, \ldots, X_5 \mid C) = P(X_1 \mid C) \cdot P(X_2 \mid C) \cdot \cdots \cdot P(X_5 \mid C) \]

- What if we have seen no training documents with the word \textit{muscle-ache} and classified in the topic \textit{Flu}?

\[ \hat{P}(X_5 = t \mid C = \text{nf}) = \frac{N(X_5 = t, C = \text{nf})}{N(C = \text{nf})} = 0 \]

- 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

\[
\hat{P}(x_{i,k} \mid c_j) = \frac{N(X_i = x_{i,k}, C = c_j) + mp_{i,k}}{N(C = c_j) + m}
\]

overall fraction in data where \(X_i=x_{i,k}\)

extent of "smoothing"\(^{23}\)
Stochastic Language Models

- Model *probability* of generating strings (each word in turn) in a language (commonly all strings over alphabet $\Sigma$). E.g., a unigram model

Model $M$

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2</td>
<td>the</td>
<td>the</td>
<td>man</td>
<td>likes</td>
</tr>
<tr>
<td>0.1</td>
<td>a</td>
<td></td>
<td>man</td>
<td>0.2</td>
</tr>
<tr>
<td>0.01</td>
<td>man</td>
<td></td>
<td></td>
<td>0.01</td>
</tr>
<tr>
<td>0.01</td>
<td>woman</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.03</td>
<td>said</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.02</td>
<td>likes</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

... multiply

$$P(s \mid M) = 0.00000008$$
Stochastic Language Models

- Model *probability* of generating any string

<table>
<thead>
<tr>
<th>Model M1</th>
<th>Model M2</th>
<th>the</th>
<th>class</th>
<th>pleaseth</th>
<th>yon</th>
<th>maiden</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2 the</td>
<td>0.2 the</td>
<td>0.2</td>
<td>0.01</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0005</td>
</tr>
<tr>
<td>0.01 class</td>
<td>0.0001 class</td>
<td>0.01</td>
<td>0.005</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
<tr>
<td>0.0001 sayst</td>
<td>0.03 sayst</td>
<td>0.02</td>
<td>0.02</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
<tr>
<td>0.0001 pleaseth</td>
<td>0.0001 pleaseth</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.0001 yon</td>
<td>0.1 yon</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.0005 maiden</td>
<td>0.01 maiden</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.01 woman</td>
<td>0.0001 woman</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\[ P(s|M2) > P(s|M1) \]
Unigram and higher-order models

\[ P(\circ \circ \circ \circ) \]

\[ = P(\circ) P(\circ | \circ) P(\circ | \circ \circ) P(\circ | \circ \circ \circ) \]

- Unigram Language Models
  \[ P(\circ) P(\circ) P(\circ) P(\circ) \]

- Bigram (generally, n-gram) Language Models
  \[ P(\circ) P(\circ | \circ) P(\circ | \circ) P(\circ | \circ ) \]

- Other Language Models
  - Grammar-based models (PCFGs), etc.
    - Probably not the first thing to try in IR
Naïve Bayes via a class conditional language model = multinomial NB

- Effectively, the probability of each class is done as a class-specific unigram language model
Using Multinomial Naive Bayes Classifiers to Classify Text: Basic method

- Attributes are text positions, values are words.

$$c_{NB} = \arg\max_{c_j \in C} P(c_j) \prod_{i} P(x_i \mid c_j)$$

$$= \arg\max_{c_j \in C} P(c_j) P(x_1 = "our" \mid c_j) \cdots P(x_n = "text" \mid c_j)$$

- Still too many possibilities
- Assume that classification is independent of the positions of the words
  - Use same parameters for each position
  - Result is bag of words model (over tokens not types)
Naive Bayes: Learning

- From training corpus, extract *Vocabulary*
- Calculate required $P(c_j)$ and $P(x_k \mid c_j)$ terms
  - For each $c_j$ 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*
  - $n_k \leftarrow$ number of occurrences of $x_k$ in $Text_j$
  - 
    $$P(x_k \mid c_j) \leftarrow \frac{n_k + \alpha}{n + \alpha |\text{Vocabulary}|}$$
Naive Bayes: Classifying

- positions ← all word positions in current document which contain tokens found in *Vocabulary*
- Return \( c_{NB} \), where

\[
c_{NB} = \arg\max_{c_j \in C} P(c_j) \prod_{i \in \text{positions}} P(x_i \mid c_j)
\]
Naive Bayes: Time Complexity

- **Training Time:** $O(|D|L_{ave} + |C||V|)$
  
  where $L_{ave}$ is the average length of a document in $D$.
  
  - Assumes all counts are pre-computed in $O(|D|L_{ave})$ time during one pass through all of the data.
  
  - Generally just $O(|D|L_{ave})$ since usually $|C||V| < |D|L_{ave}$

- **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: using logs

- 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.

\[
c_{NB} = \arg\max_{c_j \in C} [\log P(c_j) + \sum_{i \in \text{positions}} \log P(x_i | c_j)]
\]

- Note that model is now just max of sum of weights...
Naive Bayes Classifier

\[
c_{NB} = \arg\max_{c_j \in C} \left[ \log P(c_j) + \sum_{i \in \text{positions}} \log P(x_i | c_j) \right]
\]

- Simple interpretation: Each conditional parameter \( \log P(x_i | c_j) \) is a weight that indicates how good an indicator \( x_i \) is for \( c_j \).
- The prior \( \log P(c_j) \) is a weight that indicates the relative frequency of \( c_j \).
- The sum is then a measure of how much evidence there is for the document being in the class.
- We select the class with the most evidence for it.
Two Naive Bayes Models

- Model 1: Multivariate Bernoulli
  - One feature $X_w$ for each word in dictionary
  - $X_w = \text{true}$ in document $d$ if $w$ appears in $d$
  - Naive Bayes assumption:
    - Given the document’s topic, appearance of one word in the document tells us nothing about chances that another word appears

- This is the model used in the binary independence model in classic probabilistic relevance feedback on hand-classified data (Maron in IR was a very early user of NB)
Two Models

- Model 2: Multinomial = Class conditional unigram
  - One feature $X_i$ for each word pos 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, word in one position in the document tells us nothing about words in other positions
  - Second assumption:
    - Word appearance does not depend on position

\[
P(X_i = w \mid c) = P(X_j = w \mid c)
\]

*for all positions $i, j$, word $w$, and class $c*

- Just have one multinomial feature predicting all words
Parameter estimation

- Multivariate Bernoulli model:
  \[ \hat{P}(X_w = t \mid c_j) = \text{fraction of documents of topic } c_j \text{ in which word } w \text{ appears} \]

- Multinomial model:
  \[ \hat{P}(X_i = w \mid c_j) = \text{fraction of times in which word } w \text{ appears among all words in documents of topic } c_j \]
  
  - 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 feasible
  - 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 ($\chi^2$)
  - Information theory:
    - How much information does the value of one categorical variable give you about the value of another
    - Mutual information

- They’re similar, but $\chi^2$ measures confidence in association, (based on available statistics), while MI measures extent of association (assuming perfect knowledge of probabilities)
\\( \chi^2 \) statistic (CHI)

- \( \chi^2 \) 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 is rejected with confidence .999,
- since 12.9 > 10.83 (the value for .999 confidence).

<table>
<thead>
<tr>
<th></th>
<th>Term = jaguar</th>
<th>Term ≠ jaguar</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class = auto</td>
<td>2 (0.25)</td>
<td>500 (502)</td>
</tr>
<tr>
<td>Class ≠ auto</td>
<td>3 (4.75)</td>
<td>9500 (9498)</td>
</tr>
</tbody>
</table>

\[\text{observed: } f_o\] \[\text{expected: } f_e\]
### $\chi^2$ statistic (CHI)

There is a simpler formula for 2x2 $\chi^2$:

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

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$A$</td>
<td>$C$</td>
</tr>
<tr>
<td>$B$</td>
<td>$D$</td>
</tr>
</tbody>
</table>

$A = \#(t,c)$  \quad  $C = \#(\neg t,c)$  

$B = \#(t,\neg c)$  \quad  $D = \#(\neg t, \neg c)$

$N = A + B + C + D$

Value for complete independence of term and category?
Feature selection via Mutual Information

- In training set, choose $k$ words which best discriminate (give most info on) the categories.

- The Mutual Information between a word, class is:

\[
I(w, c) = \sum_{e_w \in \{0,1\}} \sum_{e_c \in \{0,1\}} p(e_w, e_c) \log \frac{p(e_w, e_c)}{p(e_w)p(e_c)}
\]

- For each word $w$ and each category $c$
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 rare uninformative terms

- Chi-square
  - Statistical foundation
  - May select very slightly informative frequent terms that are not very useful for classification

- Just use the commonest terms?
  - No particular foundation
  - In practice, this is often 90% as good
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).
  - Sometimes use cross-validation (averaging results over multiple training and test splits of the overall data)
- It’s easy to get good performance on a test set that was available to the learner during training (e.g., just memorize the test set).
- Measures: precision, recall, F1, classification accuracy
- *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
  - Otherwise F measure for each class
## Naive Bayes vs. other methods

<table>
<thead>
<tr>
<th>(a)</th>
<th>NB</th>
<th>Rocchio</th>
<th>kNN</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>micro-avg-L (90 classes)</td>
<td>80</td>
<td>85</td>
<td>86</td>
<td>89</td>
</tr>
<tr>
<td>macro-avg (90 classes)</td>
<td>47</td>
<td>59</td>
<td>60</td>
<td>60</td>
</tr>
</tbody>
</table>

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

Evaluation measure: $F_1$
Naive Bayes does pretty well, but some methods beat it consistently (e.g., SVM).
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:

<table>
<thead>
<tr>
<th></th>
<th>Student</th>
<th>Faculty</th>
<th>Person</th>
<th>Project</th>
<th>Course</th>
<th>Departm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extracted</td>
<td>180</td>
<td>66</td>
<td>246</td>
<td>99</td>
<td>28</td>
<td>1</td>
</tr>
<tr>
<td>Correct</td>
<td>130</td>
<td>28</td>
<td>194</td>
<td>72</td>
<td>25</td>
<td>1</td>
</tr>
<tr>
<td>Accuracy:</td>
<td>72%</td>
<td>42%</td>
<td>79%</td>
<td>73%</td>
<td>89%</td>
<td>100%</td>
</tr>
</tbody>
</table>
NB Model Comparison: WebKB
<table>
<thead>
<tr>
<th>Faculty</th>
<th>Students</th>
<th>Courses</th>
</tr>
</thead>
<tbody>
<tr>
<td>associate</td>
<td>resume</td>
<td>homework</td>
</tr>
<tr>
<td>chair</td>
<td>advisor</td>
<td>syllabus</td>
</tr>
<tr>
<td>member</td>
<td>student</td>
<td>assignments</td>
</tr>
<tr>
<td>ph</td>
<td>working</td>
<td>exam</td>
</tr>
<tr>
<td>director</td>
<td>stuff</td>
<td>grading</td>
</tr>
<tr>
<td>fax</td>
<td>links</td>
<td>midterm</td>
</tr>
<tr>
<td>journal</td>
<td>homepage</td>
<td>pm</td>
</tr>
<tr>
<td>recent</td>
<td>interests</td>
<td>instructor</td>
</tr>
<tr>
<td>received</td>
<td>personal</td>
<td>due</td>
</tr>
<tr>
<td>award</td>
<td>favorite</td>
<td>final</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Departments</th>
<th>Research Projects</th>
<th>Others</th>
</tr>
</thead>
<tbody>
<tr>
<td>departmental</td>
<td>investigators</td>
<td>type</td>
</tr>
<tr>
<td>colloquia</td>
<td>group</td>
<td>jan</td>
</tr>
<tr>
<td>apartment</td>
<td>members</td>
<td>enter</td>
</tr>
<tr>
<td>seminars</td>
<td>researchers</td>
<td>random</td>
</tr>
<tr>
<td>schedules</td>
<td>laboratory</td>
<td>program</td>
</tr>
<tr>
<td>webmaster</td>
<td>develop</td>
<td>net</td>
</tr>
<tr>
<td>events</td>
<td>related</td>
<td>time</td>
</tr>
<tr>
<td>facilities</td>
<td>arpa</td>
<td>format</td>
</tr>
<tr>
<td>people</td>
<td>affiliated</td>
<td>access</td>
</tr>
<tr>
<td>postgraduate</td>
<td>project</td>
<td>begin</td>
</tr>
</tbody>
</table>
Naïve Bayes on spam email
SpamAssassin

- 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
Violation of NB Assumptions

- The independence assumptions do not really hold of documents written in natural language.
  - Conditional independence
  - Positional independence
- Examples?
Example: Sensors

**Reality**

- Raining: $P(+,+,r) = \frac{3}{8}$, $P(-,-,r) = \frac{1}{8}$
- Sunny: $P(+,+s) = \frac{1}{8}$, $P(-,-,s) = \frac{3}{8}$

**NB Model**

- **M1**: Raining?
  - $P(s) = \frac{1}{2}$
  - $P(+|s) = \frac{1}{4}$
- **M2**: Raining?
  - $P(r) = \frac{3}{4}$
  - $P(+|r) = \frac{3}{4}$

**NB FACTORS:**

- $P(r,+,+) = \frac{1}{2} \times \frac{3}{4} \times \frac{3}{4}$
- $P(s,+,+) = \frac{1}{2} \times \frac{1}{4} \times \frac{1}{4}$

**PREDICTIONS:**

- $P(r|+,+) = \frac{9}{10}$
- $P(s|+,+) = \frac{1}{10}$
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

- Naive Bayes won 1\textsuperscript{st} and 2\textsuperscript{nd} place in KDD-CUP 97 competition out of 16 systems
  - Goal: Financial services industry direct mail response prediction model: Predict if the recipient of mail will actually respond to the advertisement – 750,000 records.
- More robust to irrelevant features than many learning methods
  - Irrelevant Features cancel each other without affecting results
  - Decision Trees can suffer heavily from this.
- More robust to concept drift (changing class definition over time)
- 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: Bayes Optimal Classifier
  - Never true for text, but possible in some domains
- Very Fast Learning and Testing (basically just count the data)
- Low Storage requirements
Resources for today’s lecture

- IIR 13
  - Clear simple explanation of Naïve Bayes
- Open Calais: Automatic Semantic Tagging
  - Free (but they can keep your data), provided by Thompson/Reuters (ex-ClearForest)
- Weka: A data mining software package that includes an implementation of Naive Bayes
- Reuters-21578 – the most famous text classification evaluation set
  - Still widely used by lazy people (but now it’s too small for realistic experiments – you should use Reuters RCV1)