# Text as Data

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# Supervised Learning

1) Task
   - Classify documents to pre existing categories
   - Measure the proportion of documents in each category
2) Objective function
   - Suppose we have $K$ categories.
   - Select $N_{\text{train}}$ document to hand-label, $Y_i = k$, $\boldsymbol{Y} = (Y_1, Y_2, \ldots, Y_{N_{\text{train}}})$

$$\boldsymbol{Y} = f(\boldsymbol{X}, \boldsymbol{\theta})$$

3) Optimization
   - Method specific: MLE, Bayesian, EM, ...
   - We learn $\widehat{\boldsymbol{\theta}}$
4) Validation
   - Obtain predicted fit for new data $f(\boldsymbol{X}_i, \widehat{\boldsymbol{\theta}})$
   - Examine prediction performance $\rightsquigarrow$ compare classification to gold standard

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- Models for discovery
  - Infer categories
  - Infer document assignment to categories
  - Pre-estimation: relatively little work
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  - Pre-estimation: extensive work constructing categories, building classifiers
  - Post-estimation: relatively little work

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Methods generalize beyond text

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3) Set of unlabeled documents
4) Method to extrapolate from hand coding to unlabeled documents

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    - Flow charts help simplify problems
2) Train coders to remove ambiguity, misinterpretation

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3) Assess coder agreement
4) Identify sources of disagreement, repeat

# How Do We Identify Coding Disagreement?

Many measures of inter-coder agreement

Essentially attempt to summarize a confusion matrix

| | Cat 1 | Cat 2 | Cat 3 | Cat 4 | Sum, Coder 1 |
|---|---|---|---|---|---|
| Cat 1 | **30** | 0 | 1 | 0 | 31 |
| Cat 2 | 1 | **1** | 0 | 0 | 2 |
| Cat 3 | 0 | 0 | **1** | 0 | 1 |
| Cat 4 | 3 | 1 | 0 | **7** | 11 |
| Sum, Coder 2 | 34 | 2 | 2 | 7 | Total: **45** |

- **Diagonal**: coders agree on document
- Off-diagonal : coders disagree (confused) on document

Generalize across ($k$) coders:

- $\frac{k(k-1)}{2}$ pairwise comparisons
- $k$ comparisons: Coder A against All other coders

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| | Coder A | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **Tot** |
| Coder B | | | | | | | | | |
| **1** | **15** | 2 | 1 | 0 | 0 | 1 | 0 | 0 | |
| **3** | 1 | 0 | **0** | 1 | 0 | 0 | 0 | 0 | |
| **4** | 0 | 0 | 0 | **5** | 0 | 3 | 1 | 0 | |
| **5** | 0 | 0 | 0 | 1 | **13** | 7 | 0 | 2 | |
| **6** | 11 | 1 | 3 | 3 | 1 | **32** | 0 | 1 | |
| **7** | 1 | 0 | 0 | 0 | 0 | 13 | **26** | 36 | |
| **8** | 2 | 0 | 0 | 0 | 1 | 7 | 0 | **8** | |
| | | | | | | | | | |
| **Total** | 30 | 3 | 4 | 10 | 15 | 63 | 27 | 47 | |

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|---|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | Tota |
| Coder C | | | | | | | | | |
| **1** | **23** | 1 | 1 | 1 | 0 | 9 | 0 | 0 | |
| **2** | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | |
| **3** | 1 | 1 | **3** | 2 | 0 | 3 | 0 | 0 | |
| **4** | 0 | 0 | 0 | **4** | 0 | 8 | 1 | 0 | |
| **5** | 0 | 0 | 0 | 2 | **13** | 2 | 0 | 2 | |
| **6** | 4 | 1 | 0 | 1 | 1 | **32** | 1 | 2 | |
| **7** | 1 | 0 | 0 | 0 | 0 | 2 | **25** | 36 | |
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| | Coder C | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | Tota |
| Coder B | | | | | | | | | |
| **1** | **18** | 0 | 1 | 0 | 0 | 0 | 0 | 0 | |
| **3** | 1 | 0 | **1** | 0 | 0 | 0 | 0 | 0 | |
| **4** | 0 | 0 | 1 | **7** | 0 | 1 | 0 | 0 | |
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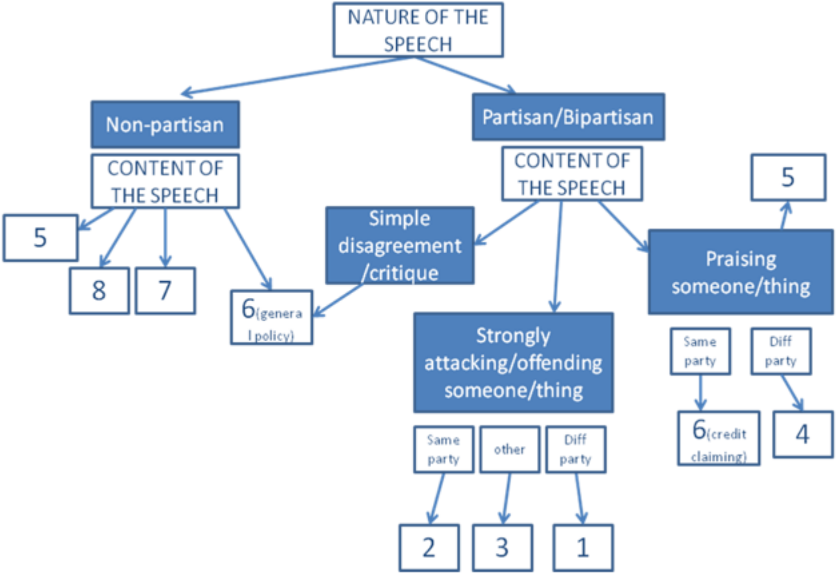
| **6** | 13 | 1 | 7 | 4 | 1 | **26** | 0 | 0 | |
| **7** | 3 | 0 | 0 | 0 | 0 | 8 | **63** | 2 | |
| **8** | 0 | 0 | 0 | 0 | 0 | 4 | 1 | **15** | |
| | | | | | | | | | |
| Total | 35 | 1 | 10 | 13 | 19 | 42 | 64 | 17 | |

# Example Coding Document

8 part coding scheme

- Across Party Taunting: explicit public and negative attacks on the other party or its members
- Within Party Taunting: explicit public and negative attacks on the same party or its members [for 1960's politics]
- Other taunting: explicit public and negative attacks not directed at a party
- Bipartisan support: praise for the other party
- Honorary Statements: qualitatively different kind of speech
- Policy speech: a speech without taunting or credit claiming
- Procedural
- No Content: (occasionally occurs in CR)

# Example Coding Document



# How Do We Summarize Confusion Matrix?

Lots of statistics to summarize confusion matrix:

- Most common: intercoder agreement

$$\text{Inter Coder}(A, B) = \frac{\text{No. (Coder A \& Coder B agree)}}{\text{No. Documents}}$$

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Best Practice: present confusion matrices.

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Calculate in R with `concord` package and function `kripp.alpha`

# How Many To Code By Hand/How Many to Code By Machine

Next week: we'll discuss how to answer this question systematically for your data set.

Rules of thumb:

- Hopkins and King (2010): 500 documents likely sufficient
- Hopkins and King (2010): 100 documents may be enough
- BUT: depends on quantity of interest
- May REQUIRE many more documents

# Percent data coded, Error (From Dan Jurafsky)

## Training size

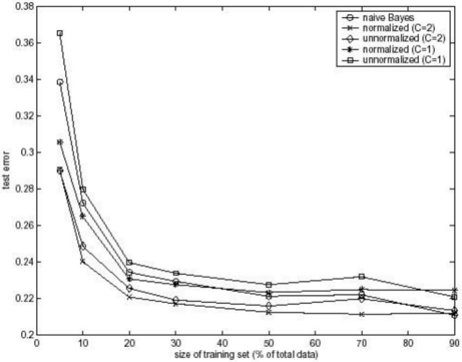


Figure 2: Test error vs training size on the newsgroups alt.atheism and talk.religion.misc

# Three categories of documents

Hand labeled

- Training set (what we'll use to estimate model)
- Validation set (what we'll use to assess model)

Unlabeled

- Test set (what we'll use the model to categorize)

Label more documents than necessary to train model

# Methods to Perform Supervised Classification

- Use the hand labels to train a statistical model.
- Naive Bayes
  - Shockingly simple application of Bayes' rule
  - Shockingly useful $\rightsquigarrow$ often default classifier

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To do this: use hand coded observations to estimate (train) regression model

# Naive Bayes and General Problem Setup

Suppose we have document $i$, ($i = 1, \ldots, N$) with $J$ features
$\boldsymbol{x}_i = (x_{1i}, x_{2i}, \ldots, x_{Ji})$
Set of $K$ categories. Category $k$ ($k = 1, \ldots, K$)
$\{C_1, C_2, \ldots, C_K\}$
Subset of labeled documents $\boldsymbol{Y} = (Y_1, Y_2, \ldots, Y_{N_{\text{train}}})$ where
$Y_i \in \{C_1, C_2, \ldots, C_K\}$.
Goal: classify every document into one category.
Learn a function that maps from space of (possible) documents to categories
To do this: use hand coded observations to estimate (train) regression model
Apply model to test data, classify those observations

# Naive Bayes and General Problem Setup (Jurafsky Inspired Slide)

Goal: For each document $\boldsymbol{x}_i$, we want to infer most likely category

$$(1)$$

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$$= \frac{\overbrace{p(C_k)}^{\text{Proportion in } C_k} \underbrace{p(\boldsymbol{x}_i|C_k)}_{\text{Language model}}}{p(\boldsymbol{x}_i)}$$

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Simple intuition about Naive Bayes:

- Learn what documents in class $j$ look like
- Find class $k$ that document $i$ is most similar to

# Naive Bayes and Unigram Language Models

Assume the following data generating process (should look familiar)

$$\begin{aligned}
\boldsymbol{\pi} &\sim \text{Dirichlet}(\boldsymbol{\alpha}) \\
\boldsymbol{\theta} &\sim \text{Dirichlet}(\boldsymbol{\lambda}) \\
\boldsymbol{\tau}_i &\sim \text{Multinomial}(1, \boldsymbol{\pi}) \\
\boldsymbol{x}_i | \tau_{ik} = 1, \boldsymbol{\theta} &\sim \text{Multinomial}(n_i, \boldsymbol{\theta}_k)
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\widehat{\pi}_k &= \frac{\sum_{i=1}^{N} I(Y_i = k) + \alpha_k}{N_{\text{train}}} \\
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$$p(\tau_{ik} = 1 | \boldsymbol{x}_i, \widehat{\boldsymbol{\pi}}, \widehat{\boldsymbol{\theta}}) \quad \propto \quad p(\tau_{ik} = 1) p(\boldsymbol{x}_i | \boldsymbol{\theta}, \tau_{ik} = 1)$$

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&\propto \overbrace{\widehat{\pi_k}}^{p(C_k)} \underbrace{\prod_{j=1}^{J} \left(\widehat{\theta}_{jk}\right)^{x_{ij}}}_{\text{Unigram model}}
\end{aligned}
$$

# Some R Code

```
library(e1071)
dep<- c(labels, rep(NA, no.testSet))
dep<- as.factor(dep)
out<- naiveBayes(dep~., as.data.frame(tdm))
predicts<- predict(out, as.data.frame(tdm[-training.set,]))
```

# Assessing Models (Elements of Statistical Learning)

- Model Selection: tuning parameters to select final model (next week's discussion)
- Model assessment : after selecting model, estimating error in classification

# Comparing Training and Validation Set

Text classification and model assessment

- Replicate classification exercise with validation set
- General principle of classification/prediction
- Compare supervised learning labels to hand labels

Confusion matrix

# Comparing Training and Validation Set

Representation of Test Statistics from Dictionary week (along with some new ones)

| | Actual Label | |
|---|---|---|
| Classification (algorithm) | Liberal | Conservative |
| Liberal | True Liberal | False Liberal |
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# ROC Curve

ROC as a measure of model performance

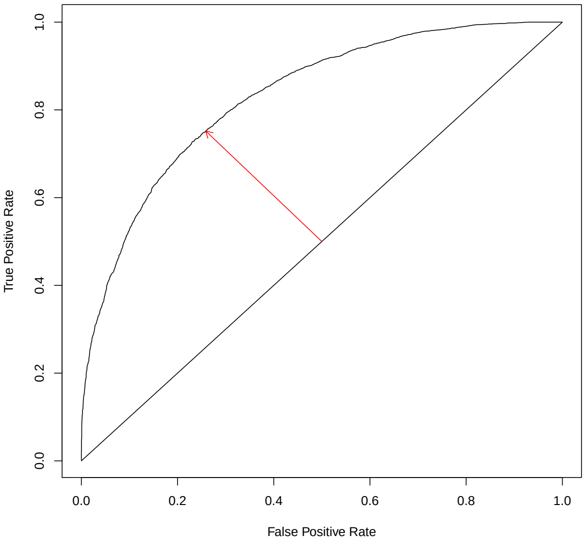
$$\text{Recall}_{\text{Liberal}} = \frac{\text{True Liberal}}{\text{True Liberal} + \text{False Conservative}}$$
$$\text{Recall}_{\text{Conservative}} = \frac{\text{True Conservative}}{\text{True Conservative} + \text{False Liberal}}$$

Tension:

- Everything liberal: $\text{Recall}_{\text{Liberal}} = 1$ ; $\text{Recall}_{\text{Conservative}} = 0$
- Everything conservative: $\text{Recall}_{\text{Liberal}} = 0$ ; $\text{Recall}_{\text{Conservative}} = 1$

Characterize Tradeoff:
Plot True Positive Rate $\text{Recall}_{\text{Liberal}}$
False Positive Rate $(1 - \text{Recall}_{\text{Conservative}})$

# Precision/Recall Tradeoff



# Simple Classification Example

Analyzing house press releases
Hand Code: 1,000 press releases

- Advertising
- Credit Claiming
- Position Taking

Divide 1,000 press releases into two sets

- 500: Training set
- 500: Test set

Initial exploration: provides baseline measurement at classifier performances
Improve: through improving model fit

# Example from Ongoing Work

| | Actual Label | | |
|---|---|---|---|
| Classification (Naive Bayes) | Position Taking | Advertising | Credit Claim. |
| Position Taking | 10 | 0 | 0 |
| Advertising | 2 | 40 | 2 |
| Credit Claiming | 80 | 60 | 306 |

$$\begin{aligned}
\text{Accuracy} &= \frac{10+40+306}{500} = 0.71 \\
\text{Precision}_{PT} &= \frac{10}{10} = 1 \\
\text{Recall}_{PT} &= \frac{10}{10+2+80} = 0.11 \\
\text{Precision}_{AD} &= \frac{40}{40+2+2} = 0.91 \\
\text{Recall}_{AD} &= \frac{40}{40+60} = 0.4 \\
\text{Precision}_{Credit} &= \frac{306}{306+80+60} = 0.67 \\
\text{Recall}_{Credit} &= \frac{306}{306+2} = 0.99
\end{aligned}$$

# Fit Statistics in R

`RWeka` library provides **Amazing** functionality.

We'll have more to say on how to install, use this next week!