Text as Data

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Discovery and Measurement

What is the research process? (Grimmer, Roberts, and Stewart 2017)

1) Discovery: a hypothesis or view of the world
2) Measurement according to some organization
3) Causal Inference: effect of some intervention

Text as data methods assist at each stage of research process

Measurement

Two approaches to measurement

1) Use an existing classification scheme to categorize documents (Today and Tuesday)
2) Simultaneously discover categories and measure prevalence (repurpose discovery methods) (Wednesday)

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- Taunting in floor statements
  $\Rightarrow$ { Partisan Taunt, Intra party taunt, Agency taunt, ... }
- Negative campaigning
  $\Rightarrow$ { Negative ad, Positive ad}

Pre-existing word weights$\rightsquigarrow$ Dictionaries

Pre-existing word weights⇝ Dictionaries

DICTION

DICTION is a computer-aided text analysis program for Windows® and Mac® that uses a series of dictionaries to search a passage for five semantic features—Activity, Optimism, Certainty, Realism and Commonality—as well as thirty-five sub-features. DICTION uses predefined dictionaries and can use up to thirty custom dictionaries built with words that the user has defined, such as topical or negative words, for particular research needs.

Pre-existing word weights $\rightsquigarrow$ Dictionaries

`DICTION`

DICTION 7, now with *Power Mode,* can read a variety of text formats and can accept a large number o
files within a single project. Projects containing over 1000 files are analyzed using *power analysis* for enhanced speed and reporting efficiency, with results automatically exported to .csv-formatted spreadsheet file.

Pre-existing word weights$\rightsquigarrow$ Dictionaries

`DICTION`

On an average computer, DICTION can process over 20,000 passages in about five minutes. DICTION requires 4.9 MB of memory and 38.4 MB of hard disk space.

Pre-existing word weights⇝ Dictionaries

DICTION

> “provides both social scientific and humanistic understandings"
> —Don Waisanen, Baruch College

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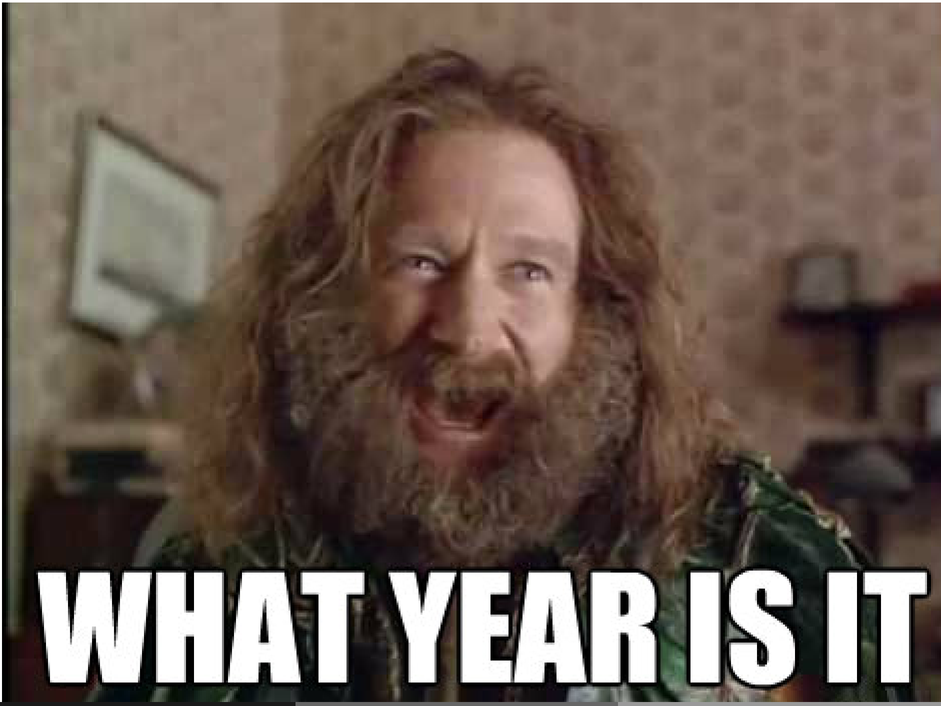
DICTION

DICTION 7 for Mac (Educational) ($219.00)

This is the educational edition of DICTION Version 7 for Mac. You
purchase on the following page.


WHAT YEAR IS IT

Dictionary Methods

Many Dictionary Methods (like DICTION)

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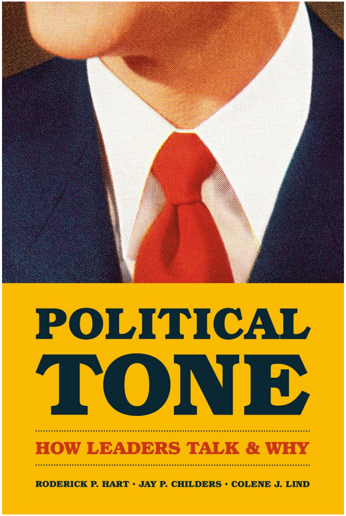
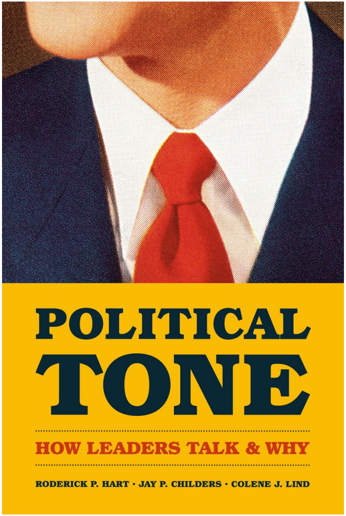
DICTION


POLITICAL
TONE
HOW LEADERS TALK & WHY
RODERICK P. HART · JAY P. CHILDERS · COLENE J. LIND

DICTION



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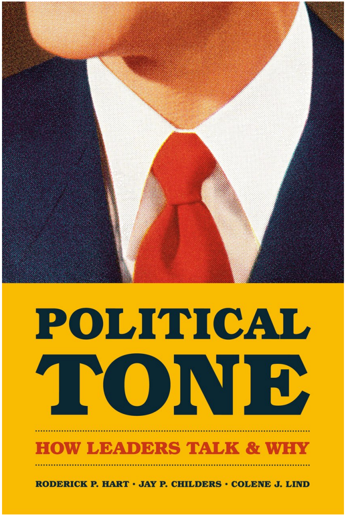

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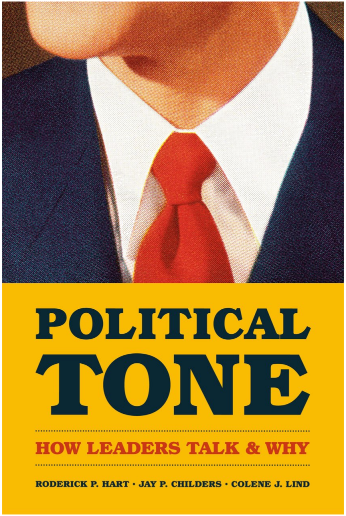

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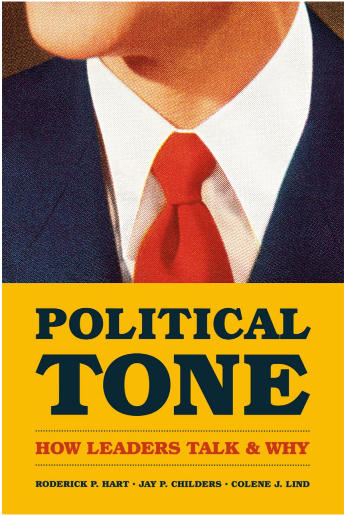

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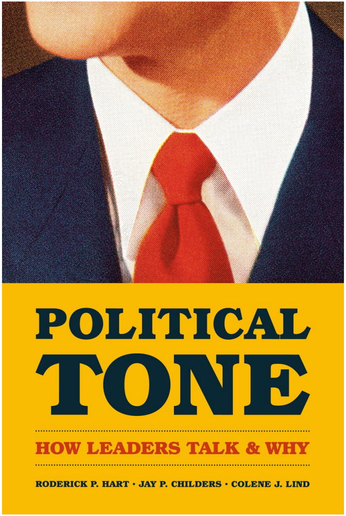

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Examine specific periods of American political history

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$$Y_i = \frac{\boldsymbol{\theta}^{'} \boldsymbol{X}_i}{\boldsymbol{X}_i^{'} \boldsymbol{1}}$$

$Y_i \approx$ continuous $\rightsquigarrow$ Classification

$Y_i > 0 \Rightarrow$ Positive Category

$Y_i < 0 \Rightarrow$ Negative Category

$Y_i \approx 0$ Ambiguous

Applying a Dictionary to Press Releases

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`Python` code and press releases

Examining Positive and Negative Statements in Press Releases

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Legislators who are more extreme $\rightsquigarrow$ less positive in press releases

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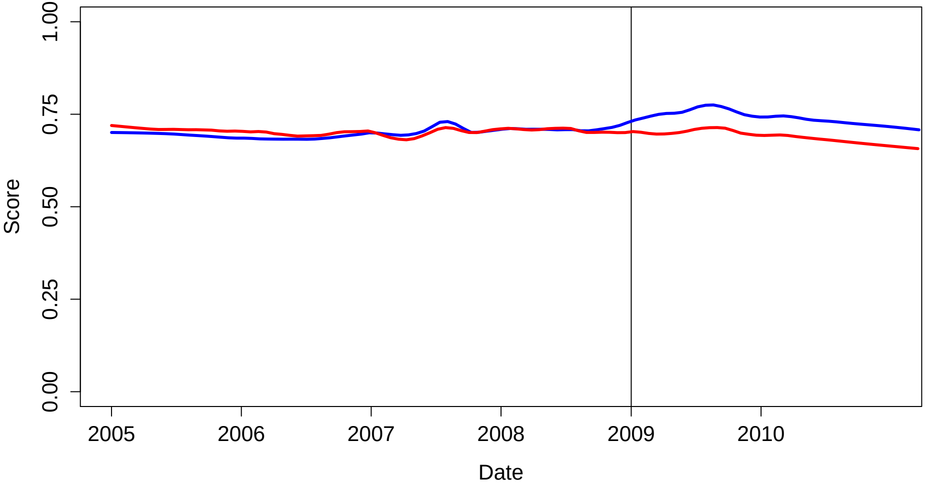

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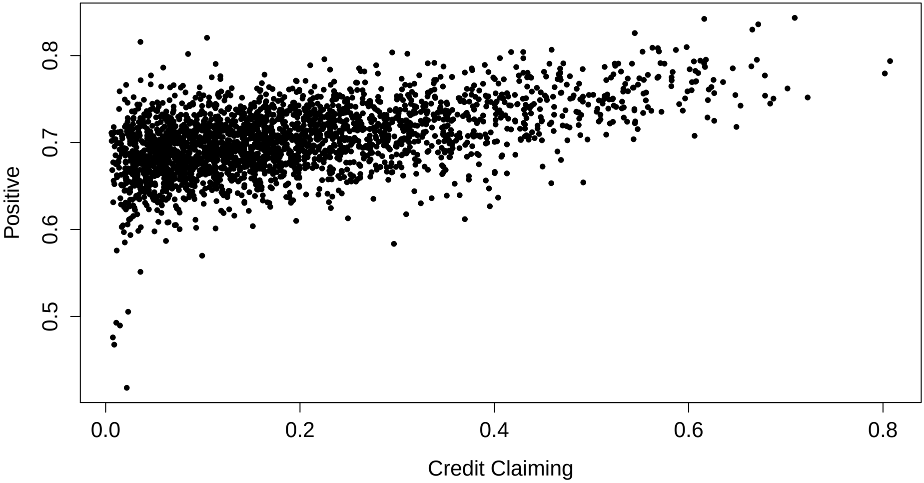

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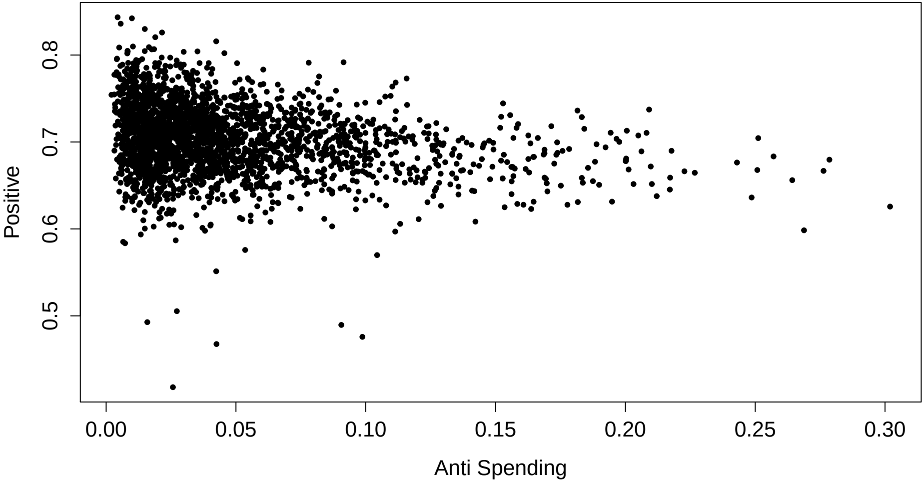

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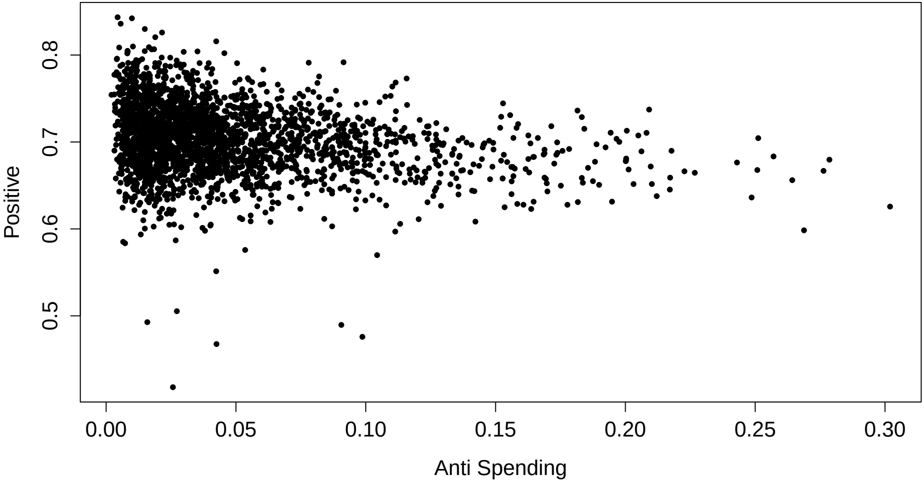

Methodological Issues/Problems with Dictionaries

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  - Ambiguity in classification rules
- A procedure for training coders:
  1) Coding rules
  2) Apply to new texts
  3) Assess coder agreement (we'll discuss more in a few weeks)
  4) Using information and discussion, revise coding rules

Assessing Classification

Measures of classification performance

	Actual Label	
Guess	Liberal	Conservative
Liberal	True Liberal	False Liberal
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Under reported for dictionary classification

What about continuous measures?

$\rightsquigarrow$

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Necessarily more complicated

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$\rightsquigarrow$

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Accounting Research: measure tone of 10-K reports

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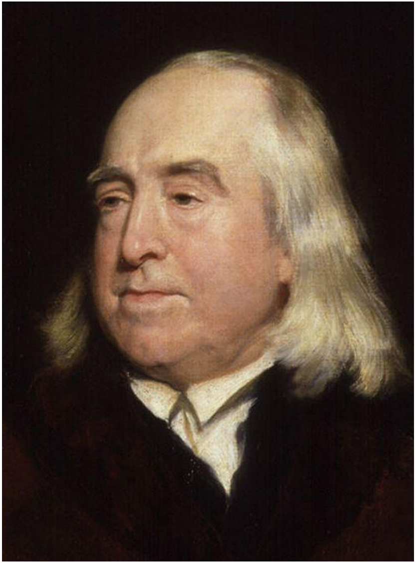
Measuring Happiness



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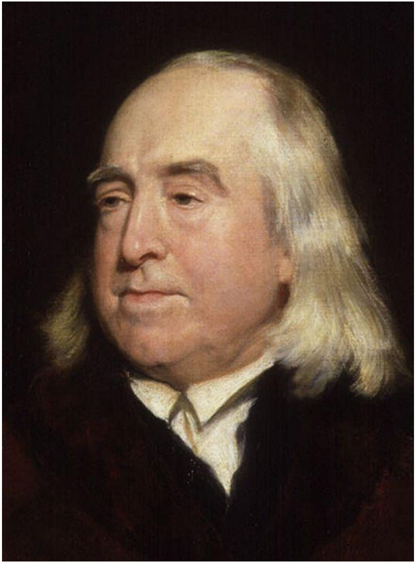

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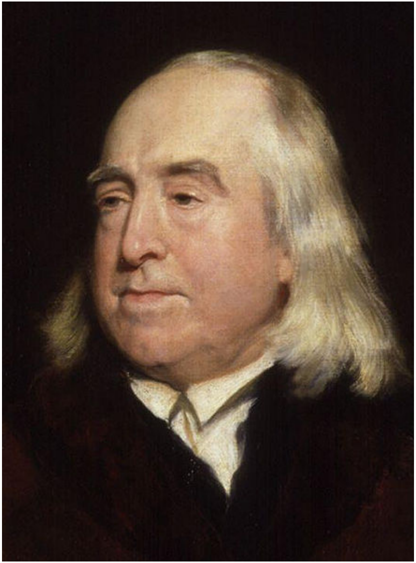

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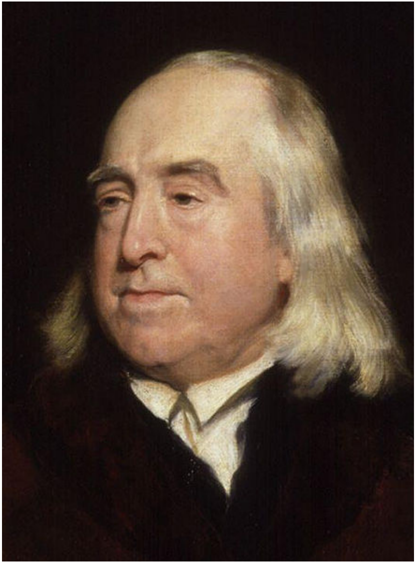

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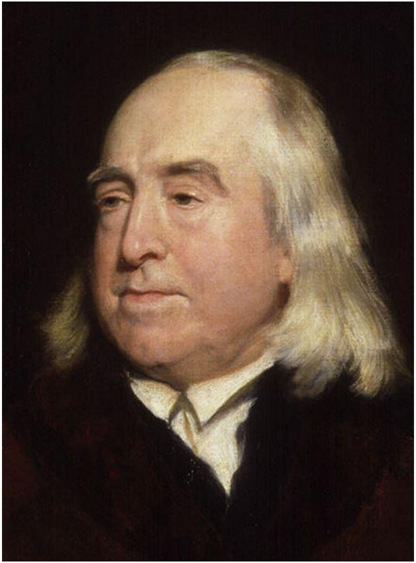

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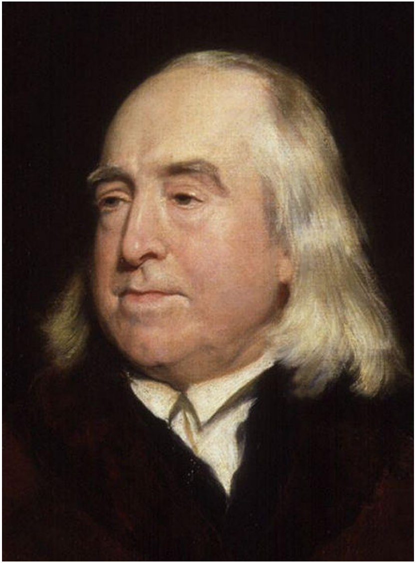

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Use Dictionary Methods

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$$\text{Happiness}_i = \frac{\sum_{k=1}^{K} \theta_k X_{ik}}{\sum_{k=1}^{K} X_{ik}}$$

Lyrics for
Michael Jackson's Billie Jean

"She was more like a beauty queen
from a movie scene.
⋮
And mother always told me,
be careful who you love.
And be careful of what you do
'cause the lie becomes the truth.
Billie Jean is not my lover,
She's just a girl who claims
that I am the one.
⋮

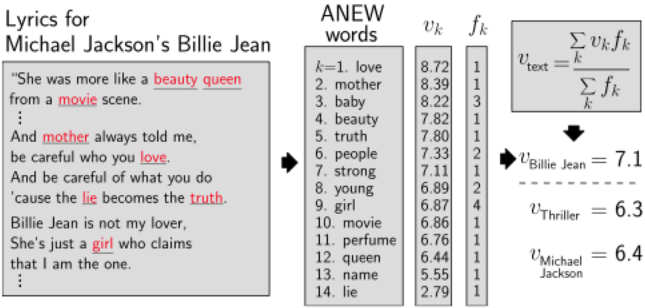
ANEW words	v_k	f_k
k=1. love	8.72	1
2. mother	8.39	1
3. baby	8.22	3
4. beauty	7.82	1
5. truth	7.80	1
6. people	7.33	2
7. strong	7.11	1
8. young	6.89	2
9. girl	6.87	4
10. movie	6.86	1
11. perfume	6.76	1
12. queen	6.44	1
13. name	5.55	1
14. lie	2.79	1

$$v_{\text{text}} = \frac{\sum_k v_k f_k}{\sum_k f_k}$$

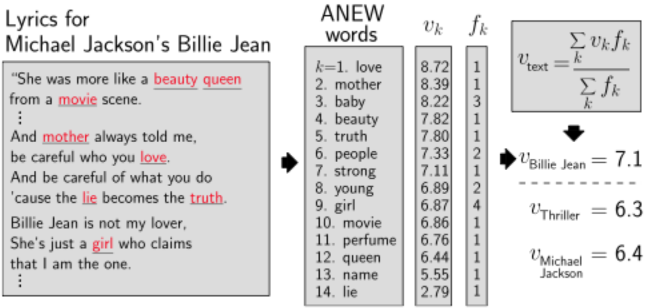
$$v_{\text{Billie Jean}} = 7.1$$

$$v_{\text{Thriller}} = 6.3$$

$$v_{\text{Michael Jackson}} = 6.4$$



Homework Hints: One approach: write a `for` loop searching for words in dictionary (caution: is dictionary stemmed?)



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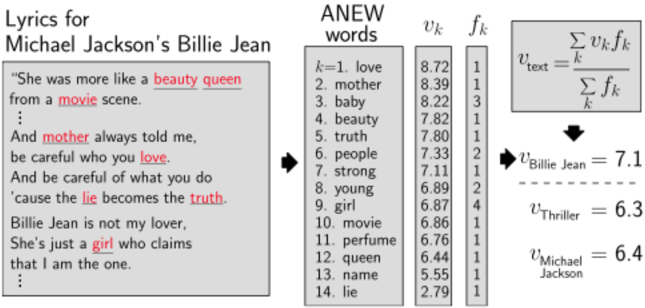

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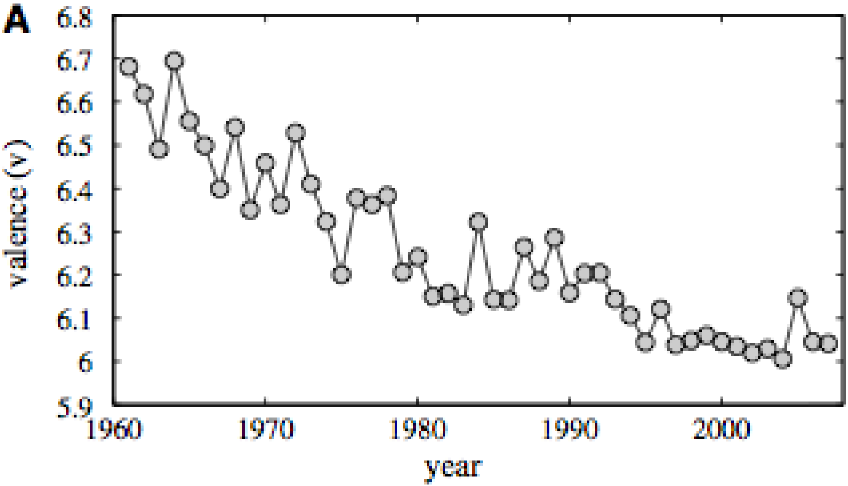
Happiest Song on Thriller?

P.Y.T. (Pretty Young Thing) (This is the right answer!)

Happiness in Society



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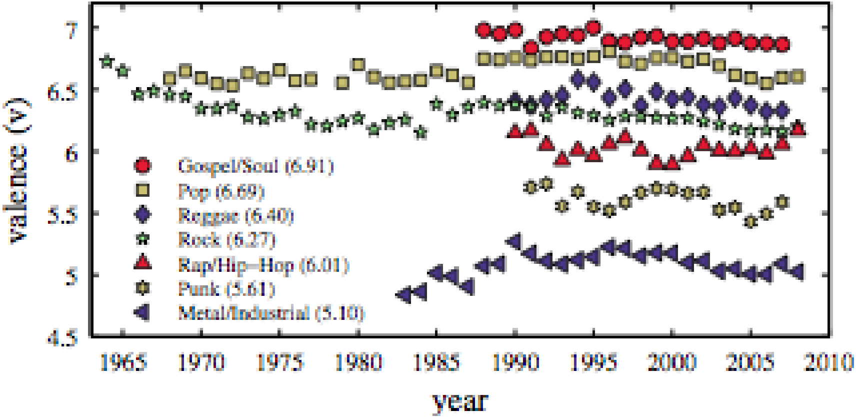

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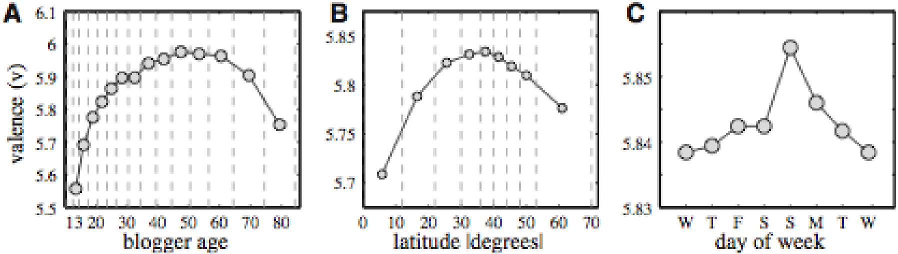

Supervised Learning

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  - Know (develop) categories before hand
  - Hand coding: assign documents to categories
  - Infer: new document assignment to categories (distribution of documents to categories)

Supervised Learning

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Methods generalize beyond text

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4) Method to extrapolate from hand coding to unlabeled documents

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For supervised methods to work: maximize coder agreement (without cheating!)

1) Write careful (and brief) coding rules
    - Flow charts help simplify problems
2) Train coders to remove ambiguity, misinterpretation

How Do We Generate Coding Rules?

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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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	Coder A								
	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	
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	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	
5	0	0	0	2	**18**	3	0	0	
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)

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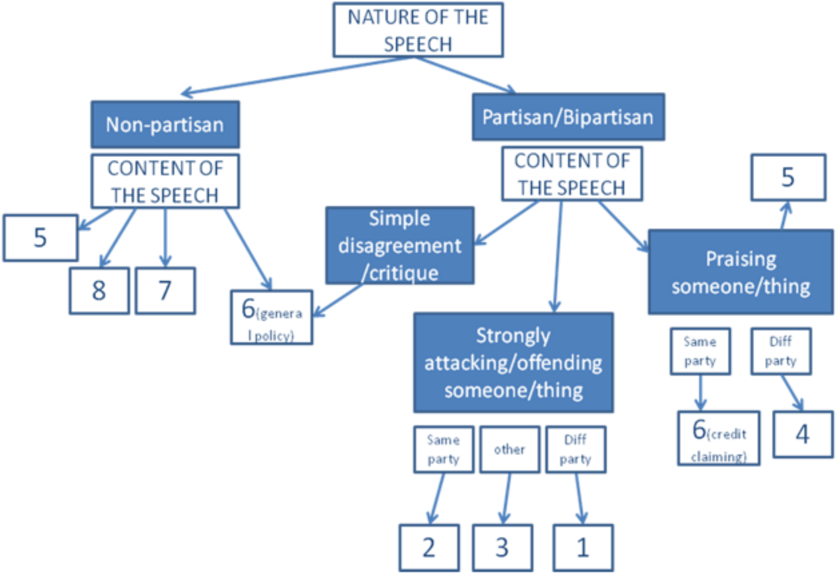

How Do We Summarize Confusion Matrix?

Lots of statistics to summarize confusion matrix:

- Most common: intercoder agreement

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

Liberal measure of agreement:

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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

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

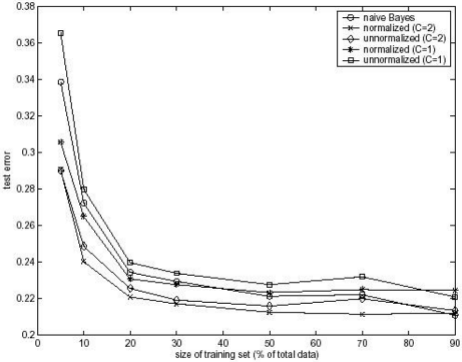

Figure 2: Test error vs training size on the newsgroups alt.atheism and talk.religion.misc

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

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Predictions will be variable

Lasso Regression Objective Function/Optimization

Penalty for Model Complexity

$$f(\boldsymbol{\beta}, \boldsymbol{X}, \boldsymbol{Y}) = \sum_{i=1}^{N} \left(y_i - \beta_0 + \sum_{j=1}^{J} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{J} \underbrace{|\beta_j|}_{\text{Penalty}}$$

Lasso Regression Objective Function/Optimization

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$$f(\boldsymbol{\beta}, \boldsymbol{X}, \boldsymbol{Y}) = \sum_{i=1}^{N} \left(y_i - \beta_0 + \sum_{j=1}^{J} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{J} \underbrace{|\beta_j|}_{\text{Penalty}}$$

- Optimization is non-linear (Absolute Value)

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- Optimization is non-linear (Absolute Value)
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  - Sub-differential, update steps
- Induces sparsity $\rightsquigarrow$ sets some coefficients to zero

Selecting λ

How do we determine λ? $\rightsquigarrow$ Cross validation

`To the R code!`

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Applying models gives score (probability) of document belong to class$\rightsquigarrow$ threshold to classify

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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
Conservative	False Conservative	True Conservative

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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:

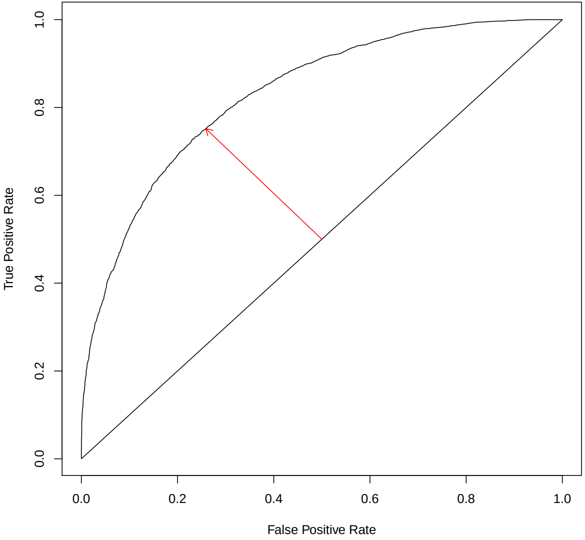
- Everything liberal: $\text{Recall}_{\text{Liberal}}$ =1 ; $\text{Recall}_{\text{Conservative}} = 0$
- Everything conservative: $\text{Recall}_{\text{Liberal}}$ =0 ; $\text{Recall}_{\text{Conservative}} = 1$

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 Grimmer, Westwood, and Messing (2014)

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

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

Naive Bayes and General Problem Setup

Suppose we have document i, ($i = 1, \ldots, N$) with J features

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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

$$(0.1)$$

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We're going to use Bayes' rule to estimate $p(C_k|\boldsymbol{x}_i)$.

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Naive Bayes and Optimization (Jurafsky Inspired Slide)

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- Imagine each x_{ij} just binary indicator. Then 2^J possible $\boldsymbol{x}_i$ documents

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p(\boldsymbol{x}_i|C_k) = \prod_{j=1}^{J} p(x_{ij}|C_k)
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Naive Bayes and Optimization (Jurafsky Inspired Slide)

Two components to estimation:

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Maximum likelihood estimation (training set):

Naive Bayes and Optimization (Jurafsky Inspired Slide)

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$$p(x_{im} = z|C_k) \quad = \quad \frac{\text{No(Docs}_{ij} = \text{z and C} = \text{C}_k \text{)}}{\text{No(C} = \text{C}_k\text{)}}$$

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Problem: What if No($\text{Docs}_{ij} = \text{z and C} = \text{C}_k$) $= 0$?

Naive Bayes and Optimization (Jurafsky Inspired Slide)

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Problem: What if No(Docs$_{ij}$ = z and C = C$_k$) = 0 ?
$\prod_{j=1}^{J} p(x_{ij}|C_k) = 0$

Naive Bayes and General Problem Setup (Jurafsky Inspired Slide)

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Solution: smoothing (Bayesian estimation)

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Algorithm steps:

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Simple intuition about Naive Bayes:

Naive Bayes and General Problem Setup (Jurafsky Inspired Slide)

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Simple intuition about Naive Bayes:

- Learn what documents in class j look like

Naive Bayes and General Problem Setup (Jurafsky Inspired Slide)

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1) Learn $\hat{p}(C)$ and $\hat{p}(\boldsymbol{x}_i|C_k)$ on training data
2) Use this to identify most likely C_k for each document i in test set

$$C_i = \text{arg max }_k \hat{p}(C_k)\hat{p}(\boldsymbol{x}_i|C_k)$$

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)

$$
\begin{aligned}
\boldsymbol{\pi} &\sim \text{Dirichlet}(\boldsymbol{\alpha}) \\
\boldsymbol{\theta} &\sim \text{Dirichlet}(\boldsymbol{\lambda}) \\
\boldsymbol{\tau}_i &\sim \text{Multinomial}(1, \boldsymbol{\pi}) \\
\boldsymbol{x}_i | \tau_{ik} = 1, \boldsymbol{\theta} &\sim \text{Multinomial}(n_i, \boldsymbol{\theta}_k)
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\widehat{\theta}_{jk} &= \frac{\sum_{i=1}^{N} I(Y_i = k) x_{ij} + \lambda_j}{\sum_{j=1}^{J} \sum_{i=1}^{N} I(Y_i = k) x_{ij} + \sum_{j=1}^{J} \lambda_j}
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$$

Naive Bayes and Unigram Language Models

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Naive Bayes and Unigram Language Models

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$$p(\tau_{ik} = 1 | \boldsymbol{x}_i, \widehat{\boldsymbol{\pi}}, \widehat{\boldsymbol{\theta}}) \quad \propto \quad p(\tau_{ik} = 1) p(\boldsymbol{x}_i | \boldsymbol{\theta}, \tau_{ik} = 1)$$

Naive Bayes and Unigram Language Models

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&\propto \widehat{\pi_k} \prod_{j=1}^{J} \left(\widehat{\theta}_{jk}\right)^{x_{ij}}
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&\propto \widehat{\pi_k} \prod_{j=1}^{J} \left(\widehat{\theta}_{jk}\right)^{x_{ij}} \\
&\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,]))
```

ReadMe: Optimization for a Different Goal (Hopkins and King 2010)

Naive Bayes, LASSO, ...: focused on individual document classification.

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Basic intuition:

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Basic intuition:

- Examine joint distribution of characteristics (without making Naive Bayes like assumption)
- Focus on distributions (only) makes this analysis possible

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Measure only presence/absence of each term [(Jx1) vector]

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- 2^J possible vectors

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Define:

$$P(\boldsymbol{x}) = \text{probability of observing } \boldsymbol{x}$$

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P(C) &= P(C_1, C_2, \ldots, C_K) \text{ target quantity of interest}
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$$\underbrace{P(\boldsymbol{x})}_{2^J x 1} = \underbrace{P(\boldsymbol{x}|C)}_{2^J x K}\underbrace{P(C)}_{K x 1}$$

Matrix algebra problem to solve, for $P(C)$
Like Naive Bayes, requires two pieces to estimate
Complication $2^J >> $ no. documents
Kernel Smoothing Methods (without a formal model)

- $P(\boldsymbol{x}) =$ estimate directly from test set
- $P(\boldsymbol{x}|C) =$ estimate from training set
  - Key assumption: $P(\boldsymbol{x}|C)$ in training set is equivalent to $P(\boldsymbol{x}|C)$ in test set
- If true, can perform biased sampling of documents, worry less about drift...

Algorithm Summarized

- Estimate $\hat{p}(\boldsymbol{x})$ from test set
- Estimate $\hat{p}(\boldsymbol{x}|C)$ from training set
- Use $\hat{p}(\boldsymbol{x})$ and $\hat{p}(\boldsymbol{x}|C)$ to solve for $p(C)$

Assessing Model Performance

Not classifying individual documents $\rightarrow$ different standards
Mean Square Error :

$$E[(\hat{\theta} - \theta)^2] = \text{var}(\hat{\theta}) + \text{Bias}(\hat{\theta}, \theta)^2$$

Suppose we have true proportions $P(C)^{\text{true}}$. Then, we'll estimate Root Mean Square Error

$$\text{RMSE} = \sqrt{\frac{\sum_{j=1}^{J} (P(C_j)^{\text{true}} - P(C_j))}{J}}$$

$$\text{Mean Abs. Prediction Error} = \left|\frac{\sum_{j=1}^{J} (P(C_j)^{\text{true}} - P(C_j))}{J}\right|$$

Visualize: plot true and estimated proportions

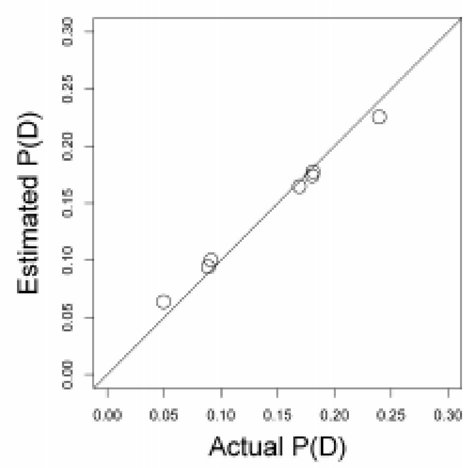
Estimated P(D)
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Actual P(D)

Table 1 **Performance of Our Nonparametric Approach and Four Support Vector Machine Analyses**

	Percent of Blog Posts Correctly Classified			
	In-Sample Fit	In-Sample Cross-Validation	Out-of-Sample Prediction	Mean Absolute Proportion Error
Nonparametric	—	—	—	1.2
Linear	67.6	55.2	49.3	7.7
Radial	67.6	54.2	49.1	7.7
Polynomial	99.7	48.9	47.8	5.3
Sigmoid	15.6	15.6	18.2	23.2

Notes: Each row is the optimal choice over numerous individual runs given a specific kernel. Leaving aside the sigmoid kernel, individual classification performance in the first three columns does not correlate with mean absolute error in the document category proportions in the last column.

Using the House Press Release Data

Method	RMSE	APSE
ReadMe	0.036	0.056
NaiveBayes	0.096	0.14
SVM	0.052	0.084

Code to Run in R

Control file:

filename	truth	trainingset
20July2009LEWIS53.txt	4	1
26July2006LEWIS249.txt	2	0

```
tdm<- undergrad(control=control, fullfreq=F)
process<- preprocess(tdm)
output<- undergrad(process)
output$est.CSMF ## proportion in each category
output$true.CSMF ## if labeled for validation set (but not
used in training set)
```