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 (This morning)
2) Simultaneously discover categories and measure prevalence (This afternoon)

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  $\Rightarrow$ { Support, Ambiguous, Oppose }
- Positions on Court Cases
  $\Rightarrow$ { Agree with Court, Disagree with Court }
- Liberal/Conservative Blog Posts
  $\Rightarrow$ { Liberal, Middle, Conservative, No Ideology Expressed }

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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⇝ Dictionaries

DICTION

DICTION 7, now with *Power Mode,* can read a variety of text formats and can accept a large number of 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⇝ 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

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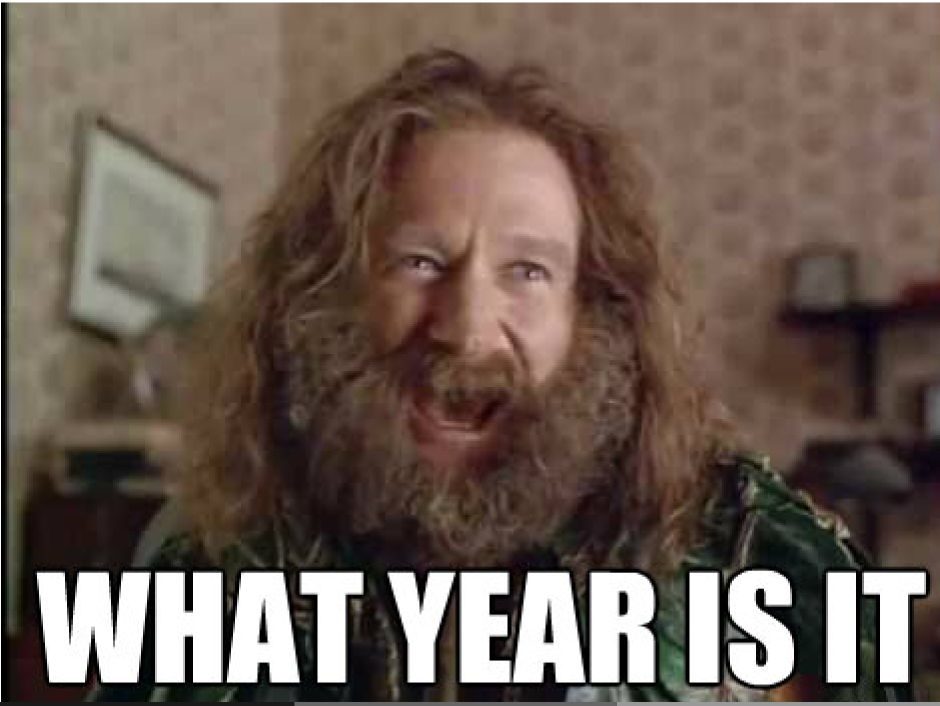
> “provides both social scientific and humanistic understandings"
>
> —Don Waisanen, Baruch College

Pre-existing word weights⇝ Dictionaries

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

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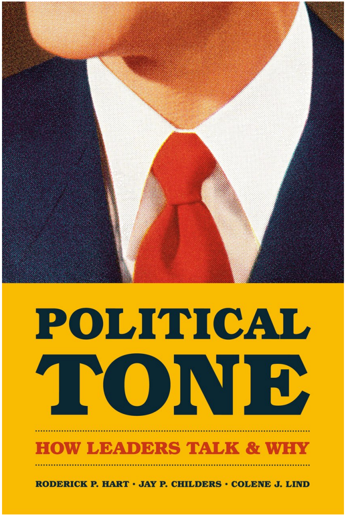
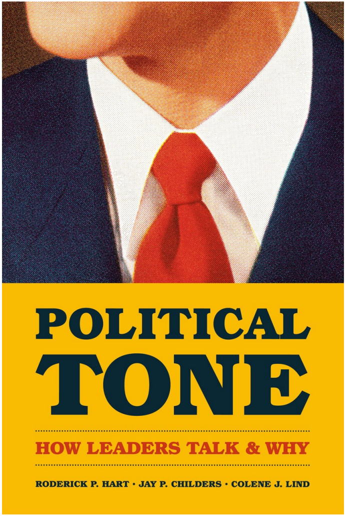

POLITICAL
TONE
HOW LEADERS TALK & WHY
RODERICK P. HART · JAY P. CHILDERS · COLENE J. LIND

DICTION



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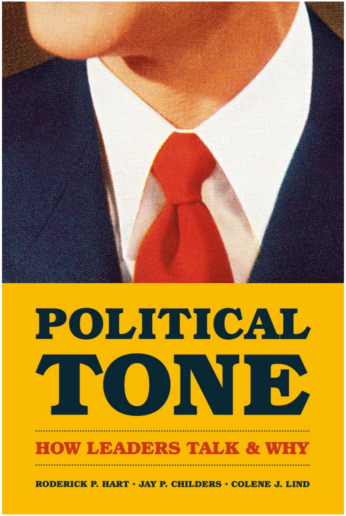

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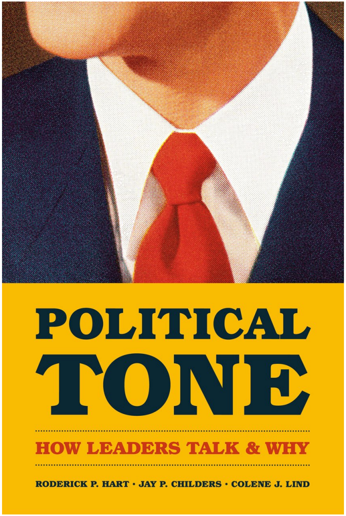

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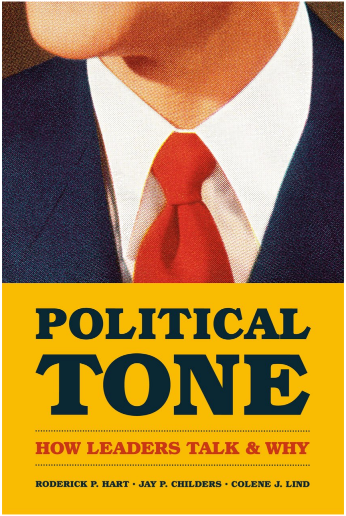

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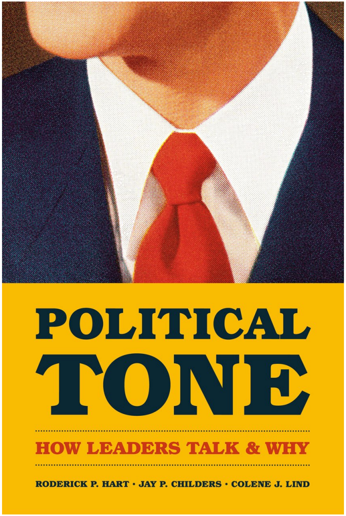

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Examine specific periods of American political history

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Y_i &= \frac{\boldsymbol{\theta}^{'} \boldsymbol{X}_i}{\boldsymbol{X}_i^{'} \mathbf{1}}
\end{aligned}
$$

$Y_i \approx$ 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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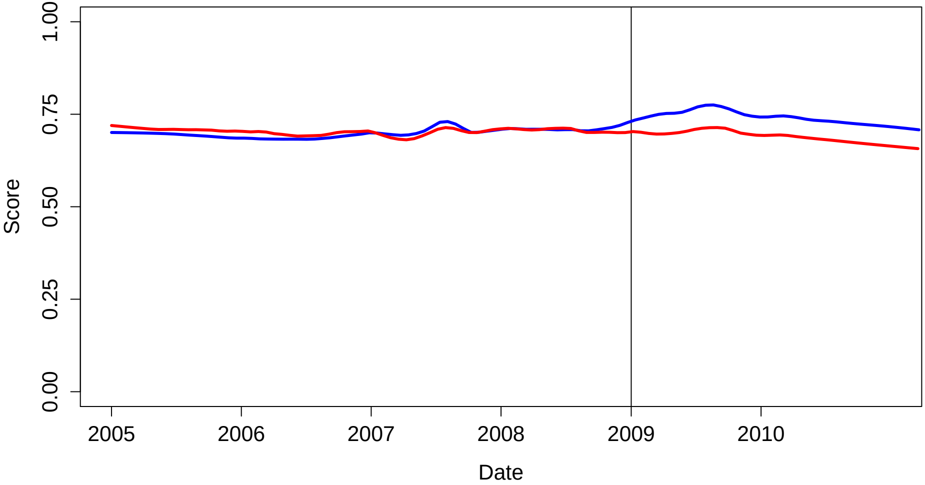

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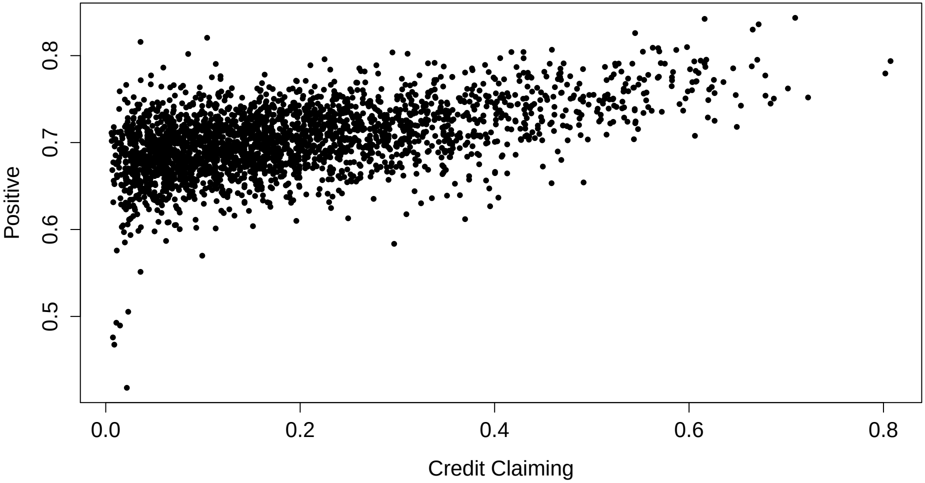

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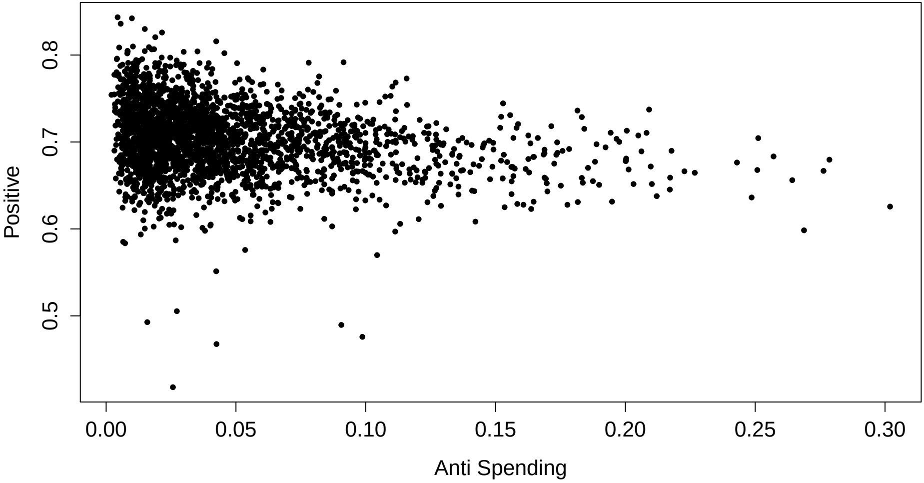

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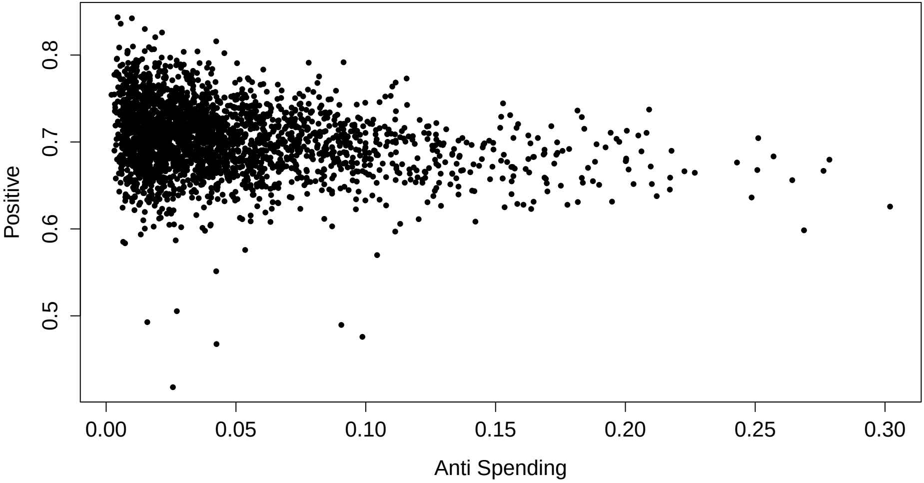

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- A procedure for training coders:
  1) Coding rules
  2) Apply to new texts
  3) Assess coder agreement (we'll discuss more in a few weeks)
  4) Using information and discussion, revise coding rules

Assessing Classification

Measures of classification performance

	Actual Label	
Guess	Liberal	Conservative
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Under reported for dictionary classification

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$\rightsquigarrow$

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Necessarily more complicated

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Accounting Research: measure tone of 10-K reports

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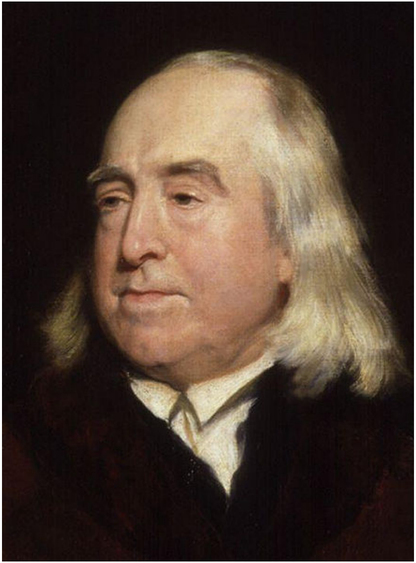
Measuring Happiness



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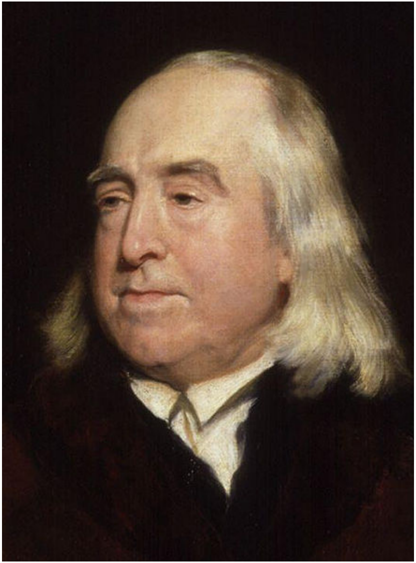

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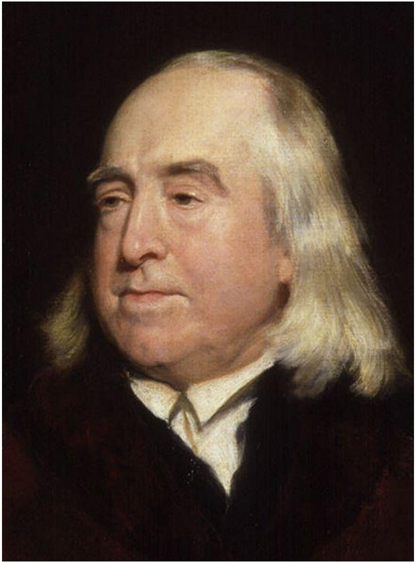

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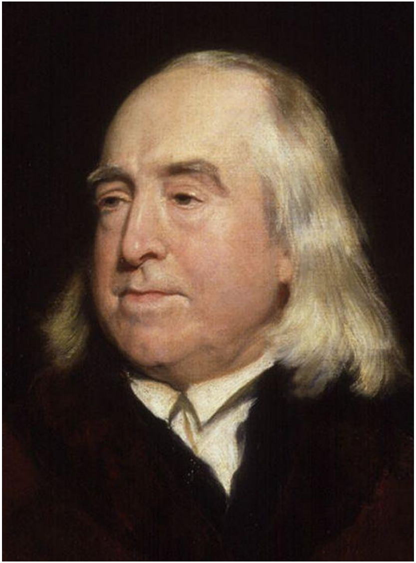

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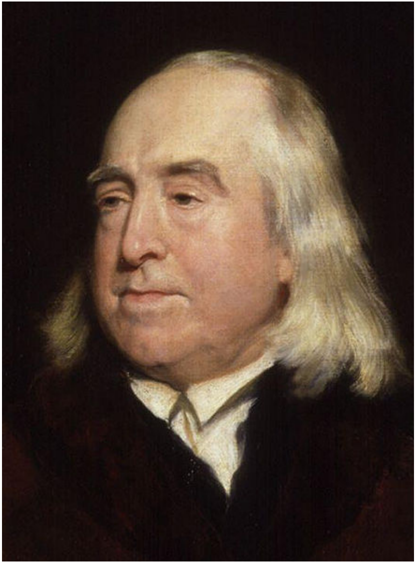

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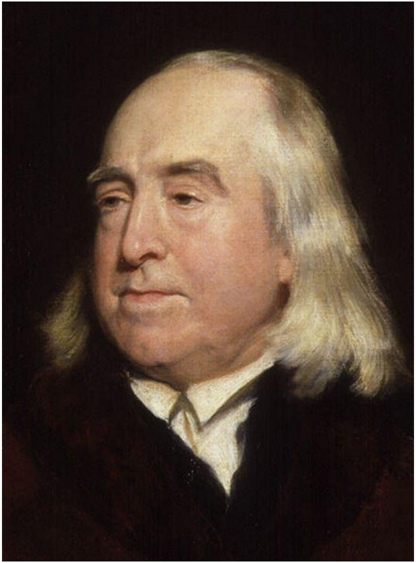

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Use Dictionary Methods

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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.
⋮

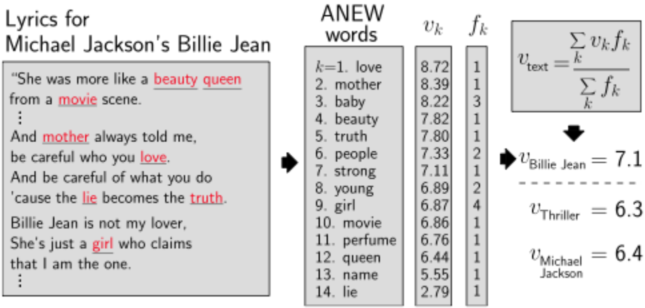
ANEW words	v_k	f_k
k=1. love	8.72	1
2. mother	8.39	1
3. baby	8.22	3
4. beauty	7.82	1
5. truth	7.80	1
6. people	7.33	2
7. strong	7.11	1
8. young	6.89	2
9. girl	6.87	4
10. movie	6.86	1
11. perfume	6.76	1
12. queen	6.44	1
13. name	5.55	1
14. lie	2.79	1

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

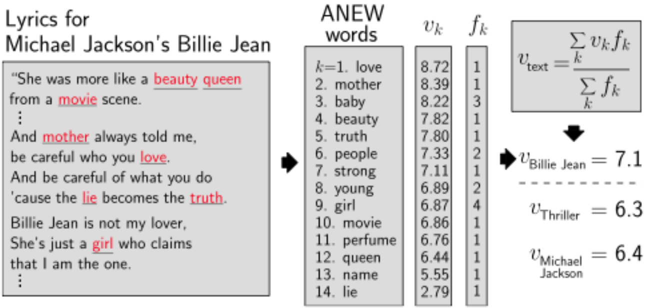
$$v_{\text{Billie Jean}} = 7.1$$

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

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



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



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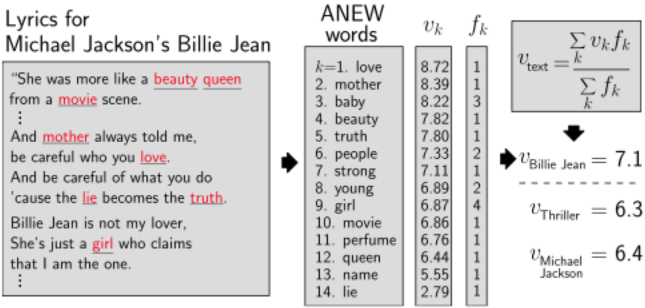
Happiest Song on Thriller?



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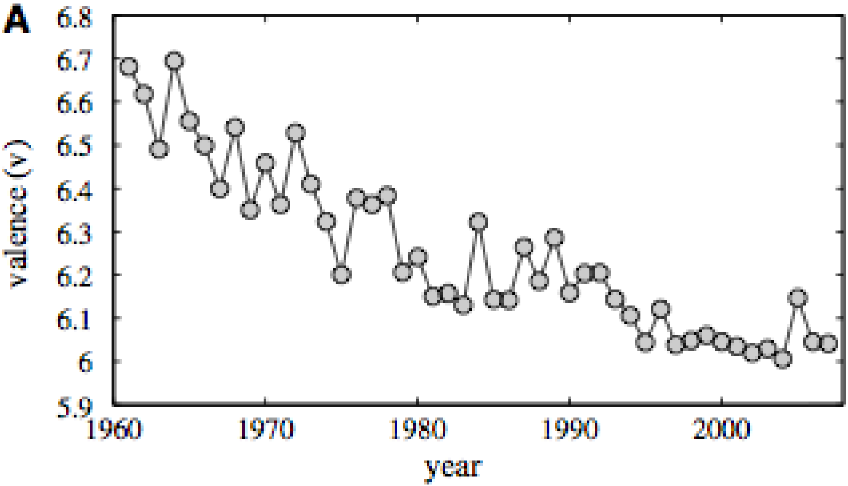
Happiest Song on Thriller?

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

Happiness in Society



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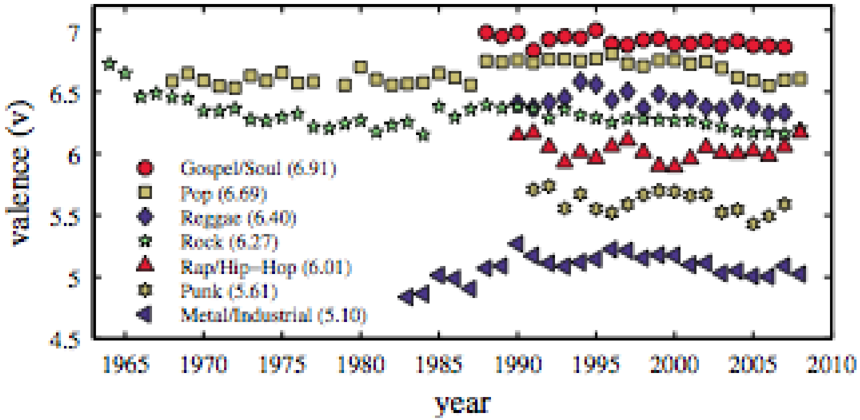

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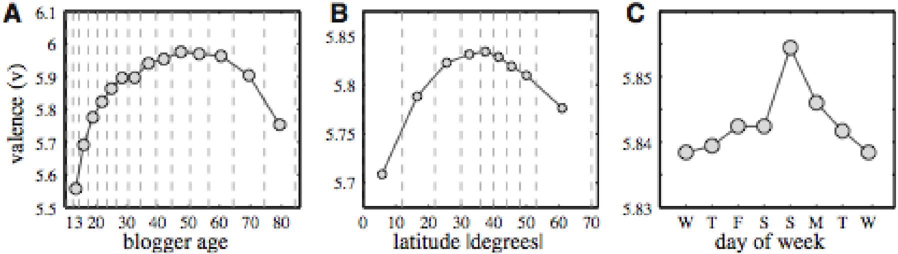

Supervised Learning

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Supervised Methods:

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- Models for categorizing texts

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    - Know (develop) categories before hand

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Supervised Methods:

- Models for categorizing texts
  - 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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- How to generate valid hand coding categories

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- How to generate valid hand coding categories
  - Assessing coder performance
  - Assessing disagreement among coders
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Methods generalize beyond text

Components to Supervised Learning Method

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4) Method to extrapolate from hand coding to unlabeled documents

How Do We Generate Coding Rules and Categories?

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Challenge: coding rules/training coders to maximize coder performance

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

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

How Do We Generate Coding Rules?

Iterative process for generating coding rules:

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- Fit Annotation model (Dawid and Skene 1979), infer parameters

Problem:

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Coder Error $\rightsquigarrow$ Biased proportions

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Solution:

- Method and easy to use software $\rightsquigarrow$ bounds on truth

What To Do About It

Measuring reliability $\rightsquigarrow$ descriptive task

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- Derive bounds on proportions, reliability $\leftrightarrow$ validity
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- Extensions for alternative settings and inferences

Motivating Example and Notation

Suppose 2 coders classify D documents into 3 categories

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Truth

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$$\pi_d \in \{1, 2, 3\}$$

$$\bar{\pi}_k = \text{mean}_d[I(\pi_d = k)],$$

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$$\text{truth} \quad = \quad \bar{\boldsymbol{\pi}}$$

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$$m_{jk}^{12} = \text{mean}_d[I(y_d^1 = j, y_d^2 = k)]$$

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The Link Between Truth and Coders' Decisions

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Coding task $\rightsquigarrow$ map from truth to codes

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The Link Between Truth and Coders' Decisions

Coding task $\rightsquigarrow$ map from truth to codes

$$\begin{aligned}
\epsilon^1_{jk} &= \text{Proportion coder 1 classifies a document in } j \text{ when truth is } k \\
\epsilon^1_{kk} &= \text{Proportion coder 1 classifies a document in } k \text{ when truth is } k
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Mapping from Truth to Coders' Decisions

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Proportion coder 2 places in category 1: mixture across categories

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$\epsilon^2_{11} = 0.8$, $\epsilon^2_{12} = 0.14$,$\epsilon^2_{13} = 0.17$ and $\bar{\boldsymbol{\pi}} = (0.7, 0.25, 0.05)$ then

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$$\bar{y}_1^2 = 0.8 \times 0.7 + 0.14 \times 0.25 + 0.17 \times 0.05 = 0.60$$

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Mapping from Truth to Coders' Decisions

$$\bar{y}^2_1 = \epsilon^2_{11}\bar{\pi}_1 + \epsilon^2_{12}\bar{\pi}_2 + \epsilon^2_{13}\bar{\pi}_3$$

Proportion coder 2 places in category 1: mixture across categories

For Example:

$\epsilon^2_{11} = 0.8$, $\epsilon^2_{12} = 0.14$,$\epsilon^2_{13} = 0.17$ and $\bar{\boldsymbol{\pi}} = (0.7, 0.25, 0.05)$ then

$$\bar{y}^2_1 = 0.8 \times 0.7 + 0.14 \times 0.25 + 0.17 \times 0.05 = 0.60$$

The Link Between Truth and Coders' Decisions

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$$\boldsymbol{E}^1 = \begin{pmatrix} 0.9 & 0.07 & 0.02 \\ 0.08 & 0.9 & 0.08 \\ 0.02 & 0.03 & 0.9 \end{pmatrix}$$

$$\boldsymbol{E}^2 = \begin{pmatrix} 0.8 & 0.14 & 0.17 \\ 0.01 & 0.80 & 0.03 \\ 0.19 & 0.06 & 0.8 \end{pmatrix}$$

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$$\begin{aligned} \bar{\boldsymbol{y}}^1 &= (0.65, 0.28, 0.07) \\ \bar{\boldsymbol{y}}^2 &= (0.6, 0.21, 0.19) \end{aligned}$$

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Problem: We don't (and can't) know evaluation matrices

Agreement, Assumptions, Structure $\rightsquigarrow$ Set of Matrices

The Link Between Truth and Reliability

Goal: use coders' reliability to infer validity

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Suppose coder 1 and coder 2 have agreement rate a^{12}.
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$$\dot{\epsilon}^{12} = \frac{1 + a^{12}}{2}$$

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Deriving Bounds on Proportions

Assumption

Wisdom of the Coders *Coder 1 and 2 have maximum validity given their agreement rate* a^{12}

$$(0.1)$$

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Intervals for the Proportion in Each Category

Set of pairs of matrices $(\tilde{\boldsymbol{E}}^1, \tilde{\boldsymbol{E}}^2)$ that satisfy maximum average validity, constant validity, and Equations **??** and **??** into set $\mathbb{E}$.

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Optimization not straightforward $\rightsquigarrow$ non-linear programming algorithm

Example 1: Three Categories

Two coders: agree 70% of speeches

	Category 1	Category 2	Category 3
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High (acceptable) reliability $\neq$ unbiased inferences

Simulation Evidence

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Maximum Validity		
100	No	0.60

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Simulation Evidence

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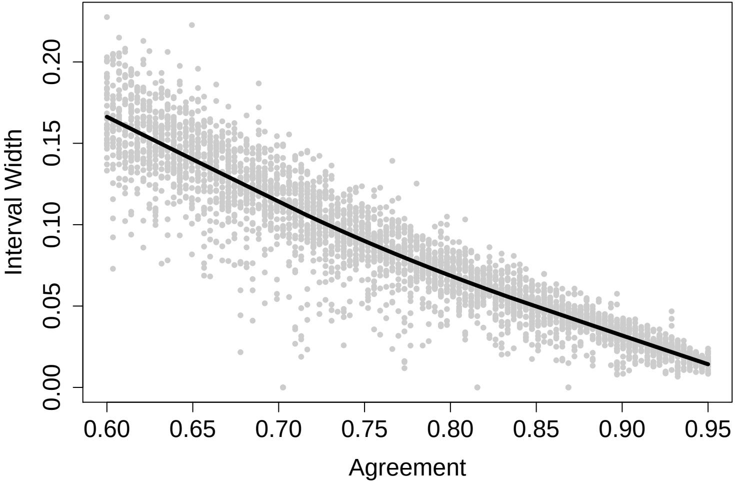
100	Yes	0.93
500	No	0.93
500	Yes	1
1000	No	0.99
1000	Yes	1
10000	No	0.98
10000	No	0.99
30000	No	1
30000	No	0.99

Simulation Evidence

No. Coded	Bootstrap	Prop. Contained
Relaxing Constant Validity		
10000	No	0.86
Independent Coders		
1000	No	1
10000	No	1



Interval Width
0.00
0.05
0.10
0.15
0.20
0.60
0.65
0.70
0.75
0.80
0.85
0.90
0.95
Agreement

Generalize:

1) Number of coders
2) Maximum Average Validity
3) Constant Validity

Dawid-Skene (1979) Annonator Model

Computer science, NLP literature

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2) Individual document labels $\rightsquigarrow$ sensitive to starting value
3) Systematic bias in inferred proportions

Criticism and Vitriol (Grimmer, King, and Superti 2015a)

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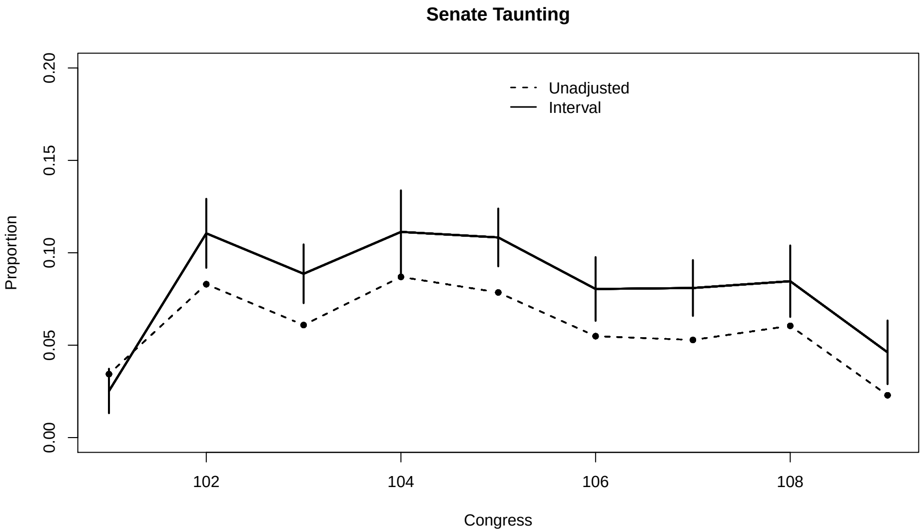
Use extensions to apply algorithm to estimate Congress-to-Congress changes in taunting rate with non-overlapping coders

Partisan Taunting



The Problem of Intercoder Reliability

Our Solution:

- Intervals that contain truth with probabilty 1
- Extensions (in the paper) include:
  - Bounds on agreement with alloyed gold standard for machine learning methods
  - Multiple coders (wisdom of crowds results)
  - Proportions as inputs to other models
- Extensions (outside paper) include:
  - Analysis of Computer Science prediction contests

The Problem of Intercoder Reliability

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Coder Error $\rightsquigarrow$ Bias

The Problem of Intercoder Reliability

Coder Error $\rightsquigarrow$ Bias

Coder Error $\rightsquigarrow$ Method to Address Bias