

# Text as Data

Justin Grimmer

Associate Professor  
Department of Political Science  
University of Chicago

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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

# Text as Data Methods for Discovery

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## Goal: Automatically Discover Organization (Similar Groups)

# Texts and Geometry

Consider a document-term matrix

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- Natural notions of **distance**
- Building block for clustering, supervised learning, and scaling

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# Vector Length



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Length2.pdf

- Pythagorean Theorem:  
Side with length  $a$

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Length3.pdf

- **Pythagorean Theorem:**  
Side with length  $a$
- Side with length  $b$  and  
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Length4.pdf

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right triangle
- $c = \sqrt{a^2 + b^2}$
- **This is generally true**



# Vector (Euclidean) Length

## Definition

Suppose  $\mathbf{v} \in \mathbb{R}^J$ . Then, we will define its *length* as

$$\begin{aligned}\|\mathbf{v}\| &= (\mathbf{v} \cdot \mathbf{v})^{1/2} \\ &= (v_1^2 + v_2^2 + v_3^2 + \dots + v_J^2)^{1/2}\end{aligned}$$

# Measures of Dissimilarity

Initial guess  $\rightsquigarrow$  Distance metrics

Properties of a metric: (distance function)  $d(\cdot, \cdot)$ . Consider arbitrary documents  $\mathbf{X}_i, \mathbf{X}_j, \mathbf{X}_k$

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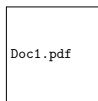
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Explore distance functions to compare documents  $\rightsquigarrow$  Do we want additional assumptions/properties?



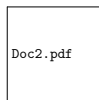
# Measuring the Distance Between Documents

## Euclidean Distance



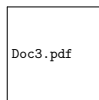
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*The Euclidean distance between documents  $\mathbf{x}_i$  and  $\mathbf{x}_j$  as*

$$\|\mathbf{x}_i - \mathbf{x}_j\| = \sqrt{\sum_{m=1}^J (x_{im} - x_{jm})^2}$$

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Suppose  $\mathbf{x}_i = (1, 4)$  and  $\mathbf{x}_j = (2, 1)$ . The distance between the documents is:

$$\begin{aligned}\|(1, 4) - (2, 1)\| &= \sqrt{(1 - 2)^2 + (4 - 1)^2} \\ &= \sqrt{10}\end{aligned}$$

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How should additional words be treated?

# Measuring Similarity



Measure 1: Inner product

# Measuring Similarity



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$$(2, 1)' \cdot (1, 4) = 6$$





Problem(?): length dependent



Fig2.pdf

**Problem**(?): length dependent

$$(4, 2)'(1, 4) = 12$$



**Problem**(?): length dependent

$$\begin{aligned}(4, 2)'(1, 4) &= 12 \\ a \cdot b &= \|a\| \times \|b\| \times \cos \theta\end{aligned}$$

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$$(0.89, 0.45)' (0.24, 0.97) = 0.65$$



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- Use training set to identify separating words (Monroe, Ideology measurement)

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- Other functional forms are fine, embed assumptions about penalization of common use



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$$\begin{aligned}\mathbf{X}_{i,\text{idf}} \cdot \mathbf{X}_{j,\text{idf}} &= (\mathbf{X}_i \times \mathbf{idf})' (\mathbf{X}_j \times \mathbf{idf}) \\ &= (\text{idf}_1^2 \times X_{i1} \times X_{j1}) + (\text{idf}_2^2 \times X_{i2} \times X_{j2}) + \\ &\quad \dots + (\text{idf}_J^2 \times X_{iJ} \times X_{jJ})\end{aligned}$$

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$$\Sigma = \begin{pmatrix} \text{idf}_1^2 & 0 & 0 & \dots & 0 \\ 0 & \text{idf}_2^2 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & \text{idf}_J^2 \end{pmatrix}$$

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If we use tf-idf for our documents, then

$$\begin{aligned} d_2(\mathbf{x}_i, \mathbf{x}_j) &= \sqrt{\sum_{m=1}^J (x_{im,\text{idf}} - x_{jm,\text{idf}})^2} \\ &= \sqrt{(\mathbf{x}_i - \mathbf{x}_j)' \Sigma (\mathbf{x}_i - \mathbf{x}_j)} \end{aligned}$$

# Final Product

Applying some measure of distance, similarity (if symmetric) yields:

$$\mathbf{D} = \begin{pmatrix} 0 & d(1,2) & d(1,3) & \dots & d(1,N) \\ d(2,1) & 0 & d(2,3) & \dots & d(2,N) \\ d(3,1) & d(3,2) & 0 & \dots & d(3,N) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ d(N,1) & d(N,2) & d(N,3) & \dots & 0 \end{pmatrix}$$

**Lower Triangle** contains unique information  $N(N-1)/2$

# Clustering

## Fully Automated Clustering

- 1) Distance metric  $\rightsquigarrow$  when are documents close?
- 2) Objective function  $\rightsquigarrow$  how do we summarize distances?
- 3) Optimization method  $\rightsquigarrow$  how do we find optimal clustering?

THERE IS NO A PRIORI OPTIMAL METHOD

Computer Assisted Clustering (Grimmer and King, 2011)

- **crucial** to combine human and computer insights

# K-Means $\rightsquigarrow$ Objective Function

$N$  documents  $\mathbf{x}_i = (x_{i1}, x_{i2}, \dots, x_{iJ})$  (normalized)

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Goal  $\rightsquigarrow$  Partition documents into  $K$  clusters.

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$\boldsymbol{\theta}_k$  = **exemplar** for cluster  $k$

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Hard Assignment



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Assume squared euclidean distance

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    - $\theta_1 = \text{Average across documents}$

# K-Means $\rightsquigarrow$ Optimization

Coordinate descent

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$$\text{Change} = f(\mathbf{X}, \mathbf{T}^t, \Theta^t) - f(\mathbf{X}, \mathbf{T}^{t-1}, \Theta^{t-1})$$

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In words: Assign each document  $\mathbf{x}_i$  to the closest center  $\theta_m^t$

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$$\boldsymbol{\theta}^{t+1} = \frac{\sum_{i=1}^N \tau_{ik} \mathbf{x}_i}{\sum_{i=1}^N \tau_{ik}}$$

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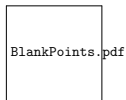
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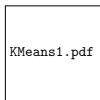
- Initialize centers
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  - Update change  $f(\mathbf{X}, \mathbf{T}^t, \boldsymbol{\Theta}^t) - f(\mathbf{X}, \mathbf{T}^{t-1}, \boldsymbol{\Theta}^{t-1})$

# Visual Example

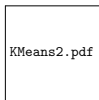




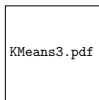
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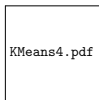
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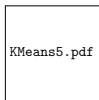
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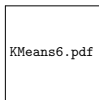
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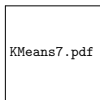
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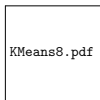
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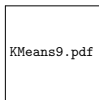


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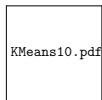




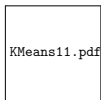
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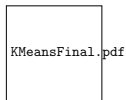
# Visual Example



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# Visual Example



# An Example: Jeff Flake

To the R Code!

# Interpreting Cluster Components

## Unsupervised methods

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Unsupervised methods  $\rightsquigarrow$  low startup costs, high post-model costs

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back to the R code!

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EM algorithm in slides appendix of Class 10 for my text as data course

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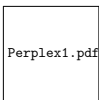
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Forthcoming)

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- Statistics: measure **cohesiveness** and **exclusivity** (Roberts, et al 2017 Forthcoming)

# What's Prediction Got to Do With It?

- Prediction  $\rightsquigarrow$  One Task
- Do we care about it?  $\rightsquigarrow$  Social science application where we're predicting new texts?
- Does it correspond to how we might use the model?

Chang et al 2009 (“Reading the Tea Leaves”) :

- Compare perplexity with **human** based evaluations
- **NEGATIVE** relationship between perplexity and human based evaluations

Different strategy  $\rightsquigarrow$  measure quality in **topics** and **clusters**

- Statistics: measure **cohesiveness** and **exclusivity** (Roberts, et al 2017 Forthcoming)
- Experiments: measure **topic** and **cluster** quality

# Experimental Approaches

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- 1) Topic Quality
- 2) Cluster Quality

# Experimental Approaches

- 1) Take  $M$  top words for a topic
- 2) Randomly select a top word from another topic
  - 2a) Sample the topic number from  $l$  from  $K - 1$  (uniform probability)
  - 2b) Sample word  $j$  from the  $M$  top words in topic  $l$
  - 2c) Permute the words and randomly insert the **intruder**:
    - List:

$$\text{test} = (v_{k,3}, v_{k,1}, v_{l,j}, v_{k,2}, v_{k,4}, v_{k,5})$$

# Example Experiment: Word Intrusion (Weiss and Grimmer, In Progress)

bowl, flooding, olympic, olympics, nfl, coach

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Deploy on Mechanical Turk

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- Select clustering with highest cluster quality
- Can be used to compare any clusterings, regardless of source

# How do we Choose $K$ ?

Generate many candidate models

- 1) Assess using numerical values
- 2) Use experiments
- 3) Read
- 4) Final decision  $\rightsquigarrow$  combination

# Computer Assisted Clustering Methods

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k-means



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k-means , Mixture of multinomials , k-medoids , affinity propagation , agglomerative Hierarchical fuzzy k-means, trimmed k-means, k-Harmonic means, fuzzy k-medoids, fuzzy k modes, maximum entropy clustering, model based hierarchical (agglomerative), proximus, ROCK, divisive hierarchical, DISMEA, Fuzzy, QTClust, self-organizing map, self-organizing tree, unnormalized spectral, MS spectral, NJW Spectral, SM Spectral, Dirichlet Process Multinomial, Dirichlet Process Normal, Dirichlet Process von-mises Fisher, Mixture of von mises-Fisher (EM), Mixture of von Mises Fisher (VA), Mixture of normals, co-clustering mutual information, co-clustering SVD, LLAhclust, CLUES, bclust, c-shell, qtClustering, LDA, Express Agenda Model, Hierarchical Dirichlet process prior, multinomial, uniform process multinomial, Chinese Restaurant Distance Dirichlet process multinomial, Pitmann-Yor Process multinomial, LSA, ...

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Deep problem in cluster analysis literature: full automation requires more information



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- Our answer: a geography of clusterings

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- 8) (Or, our new strategy: represent entire Bell space directly; no need to examine document contents )

# Crosas, Grimmer, King, and Stewart (2017) $\rightsquigarrow$ Consilience

Consilience.com example (email me for assignment + access)

# Example Discovery: What Do Members of Congress Do?

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- Data: 200 press releases from Frank Lautenberg's office (D-NJ)
- Apply our method (relying on many clustering algorithms)

# Example Discovery



# Example Discovery

Each point is a **clustering**  
Affinity Propagation-Cosine  
(Dueck and Frey 2007)



# Example Discovery



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**Close to:**

Mixture of von Mises-Fisher  
distributions (Banerjee et. al.  
2005)

⇒ Similar clustering of  
documents

# Example Discovery



Space between methods:



# Example Discovery



Space between methods:

# Example Discovery



Space between methods:  
**local cluster ensemble**

# Example Discovery



# Example Discovery



Found a **region** with clusterings  
that all reveal the same  
important insight

# Example Discovery

Mixture:



# Example Discovery

Mixture:

0.39 Hclust-Canberra-McQuitty

0.13 Hclust-Correlation-Ward

0.09 Hclust-Pearson-Ward



# Example Discovery



## Mixture:

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## Credit Claiming, Pork:

“Sens. Frank R. Lautenberg (D-NJ) and Robert Menendez (D-NJ) announced that the U.S. Department of Commerce has awarded a \$100,000 grant to the South Jersey Economic Development District”

# Example Discovery



## Credit Claiming, Legislation:

“As the Senate begins its recess, Senator Frank Lautenberg today pointed to a string of victories in Congress on his legislative agenda during this work period”

# Example Discovery



## Advertising:

“Senate Adopts  
Lautenberg/Menendez Resolution  
Honoring Spelling Bee Champion  
from New Jersey”

# Example Discovery: Partisan Taunting



**Partisan Taunting:**  
“Republicans Selling Out Nation  
on Chemical Plant Security”

# In Sample Illustration of Partisan Taunting

Important Concept Overlooked in Mayhew's (1974) typology

- “Senator Lautenberg Blasts Republicans as ‘Chicken Hawks’ ”  
[Government Oversight]



Sen. Lautenberg  
on Senate Floor  
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**Consequences for representation:** Deliberative, Polarization, Policy



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- Discovered using 200 press releases; 1 senator.

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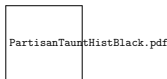
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- Demonstrate prevalence using senators' press releases.
- Apply supervised learning method: measure **proportion of press releases** a senator taunts other party

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- Demonstrate prevalence using senators' press releases.
- Apply supervised learning method: measure **proportion of press releases** a senator taunts other party

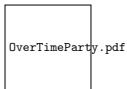


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# Over Time Tauting Rates in Speeches





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  - Observe group with most productivity 20-30 years later
- To identify limits of methods, when to use which approach, need evaluations for the **usefulness** of conceptualizations



# Stylometry ~> Who Wrote Disputed Federalist Papers?

Federalist papers ~> Mosteller and Wallace (1963)

- Persuade citizens of New York State to adopt constitution
- Canonical texts in study of American politics
- 77 essays
  - Published from 1787-1788 in Newspapers
  - And under the name **Publius**, anonymously

## Who Wrote the Federalist papers?

- Jay wrote essays 2, 3, 4,5, and 64
- Hamilton: wrote 43 papers
- Madison: wrote 12 papers

## Disputed: Hamilton or Madison?

- Essays: 49-58, 62, and 63
- Joint Essays: 18-20

**Task:** identify authors of the disputed papers.

**Task:** Classify papers as Hamilton or Madison using dictionary methods

# Setting up the Analysis

**Training**  $\rightsquigarrow$  papers Hamilton, Madison are known to have authored

**Test**  $\rightsquigarrow$  unlabeled papers

**Preprocessing:**

- Hamilton/Madison both discuss similar issues
- Differ in extent they use **stop words**
- Focus analysis on the stop words

# Setting up the Analysis

- $\mathbf{Y} = (Y_1, Y_2, \dots, Y_N) = (\text{Hamilton}, \text{Hamilton}, \text{Madison}, \dots, \text{Hamilton})$   
 $N \times 1$  matrix with author labels

- Define the number of words in federalist paper  $i$  as  $\text{num}_i$

$$\mathbf{X} = \begin{pmatrix} \frac{1}{\text{num}_1} & \frac{2}{\text{num}_1} & \frac{0}{\text{num}_1} & \cdots & \frac{3}{\text{num}_1} \\ \frac{0}{\text{num}_2} & \frac{1}{\text{num}_2} & \frac{0}{\text{num}_2} & \cdots & \frac{0}{\text{num}_2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \frac{0}{\text{num}_N} & \frac{0}{\text{num}_N} & \frac{1}{\text{num}_N} & \cdots & \frac{0}{\text{num}_N} \end{pmatrix}$$

$N \times J$  counting stop word usage rate

- $\boldsymbol{\theta} = (\theta_1, \theta_2, \dots, \theta_J)$

Word weights.

# Objective Function

**Heuristically:** find  $\theta^* = (\theta_1^*, \theta_2^*, \dots, \theta_J^*)$  used to create score

$$p_i = \sum_{j=1}^J \theta_j^* X_{ij}$$

that maximally discriminates between categories



# Objective Function

Define:

$$\mu_{\text{Madison}} = \frac{1}{N_{\text{Madison}}} \sum_{i=1}^N I(Y_i = \text{Madison}) \mathbf{x}_i$$

$$\mu_{\text{Hamilton}} = \frac{1}{N_{\text{Hamilton}}} \sum_{i=1}^N I(Y_i = \text{Hamilton}) \mathbf{x}_i$$

# Objective Function

We can then define functions that describe the “projected” mean and variance for each author

$$g(\boldsymbol{\theta}, \mathbf{X}, \mathbf{Y}, \text{Madison}) = \frac{1}{N_{\text{Madison}}} \sum_{i=1}^N I(Y_i = \text{Madison}) \boldsymbol{\theta}' \mathbf{x}_i = \boldsymbol{\theta}' \boldsymbol{\mu}_{\text{Madison}}$$

$$g(\boldsymbol{\theta}, \mathbf{X}, \mathbf{Y}, \text{Hamilton}) = \frac{1}{N_{\text{Hamilton}}} \sum_{i=1}^N I(Y_i = \text{Hamilton}) \boldsymbol{\theta}' \mathbf{x}_i = \boldsymbol{\theta}' \boldsymbol{\mu}_{\text{Hamilton}}$$

$$s(\boldsymbol{\theta}, \mathbf{X}, \mathbf{Y}, \text{Madison}) = \sum_{i=1}^N I(Y_i = \text{Madison}) (\boldsymbol{\theta}' \mathbf{x}_i - \boldsymbol{\theta}' \boldsymbol{\mu}_{\text{Madison}})^2$$

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# Objective Function $\rightsquigarrow$ Optimization

$$\begin{aligned} f(\boldsymbol{\theta}, \mathbf{X}, \mathbf{Y}) &= \frac{(g(\boldsymbol{\theta}, \mathbf{X}, \mathbf{Y}, \text{Hamilton}) - g(\boldsymbol{\theta}, \mathbf{X}, \mathbf{Y}, \text{Madison}))^2}{s(\boldsymbol{\theta}, \mathbf{X}, \mathbf{Y}, \text{Hamilton}) + s(\boldsymbol{\theta}, \mathbf{X}, \mathbf{Y}, \text{Madison})} \\ &= \frac{(\boldsymbol{\theta}'(\boldsymbol{\mu}_{\text{Hamilton}} - \boldsymbol{\mu}_{\text{Madison}}))^2}{\text{Scatter}_{\text{Hamilton}} + \text{Scatter}_{\text{Madison}}} \end{aligned}$$

**Optimization**  $\rightsquigarrow$  find  $\boldsymbol{\theta}^*$  to maximize  $f(\boldsymbol{\theta}, \mathbf{X}, \mathbf{Y})$ , assuming independence across dimensions.

**(Fisher's) Linear Discriminant Analysis**

# Optimization $\rightsquigarrow$ Word Weights

For each word  $j$ , construct weight  $\theta_j^*$ ,

$$\mu_{j,\text{Hamilton}} = \frac{\sum_{i=1}^N I(Y_i = \text{Hamilton})X_{ij}}{\sum_{j=1}^J \sum_{i=1}^N I(Y_i = \text{Hamilton})X_{ij}}$$

$$\mu_{j,\text{Madison}} = \frac{\sum_{i=1}^N I(Y_i = \text{Madison})X_{ij}}{\sum_{j=1}^J \sum_{i=1}^N I(Y_i = \text{Madison})X_{ij}}$$

$$\sigma_{j,\text{Hamilton}}^2 = \text{Var}(X_{i,j}|\text{Hamilton})$$

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We can then generate weight  $\theta_j^*$  as

$$\theta_j^* = \frac{\mu_{j,\text{Hamilton}} - \mu_{j,\text{Madison}}}{\sigma_{j,\text{Hamilton}}^2 + \sigma_{j,\text{Madison}}^2}$$



# Optimization $\rightsquigarrow$ Trimming the Dictionary

- Trimming weights: Focus on discriminating words (very simple **regularization**)
- Cut off: For all  $|\theta_j^*| < 0.025$  set  $\theta_j^* = 0$ .

# Classification $\rightsquigarrow$ Determining Authorship

For each disputed document  $i$ , compute discrimination statistic

$$p_i = \sum_{j=1}^J \theta_j^* X_{ij}$$

$p_i \rightsquigarrow$  classification (**linear discriminator**)

- Above midpoint in training set  $\rightarrow$  Hamilton text
- Below midpoint in training set  $\rightarrow$  Madison text

**Findings:** Madison is the author of the disputed federalist papers.

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**Vague** and **Difficult** to derive before hand

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- Partial answer: identify words that distinguish press releases and floor speeches

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  - Maximum: Uncertainty  $\rightarrow X_j$  is perfect predictor
  - Minimum: 0  $\rightarrow X_j$  fails to separate speeches and floor statements

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- $\log_2$ ? Encodes bits

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- Define **entropy**  $H(\text{Doc})$

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Objective function and optimization  $\rightsquigarrow$  estimate probabilities that we then place in mutual information

# A Method for Identifying Distinguishing Words

Formula for mutual information

(based on ML estimates of probabilities)

$n_p$  = Number Press Releases

$n_s$  = Number of Speeches

$D$  =  $n_p + n_s$

$n_j$  =  $\sum_{i=1}^D X_{i,j}$  (No. docs  $X_j$  appears )

$n_{-j}$  = No. docs  $X_j$  does not appear

$n_{j,p}$  = No. press and  $X_j$

$n_{j,s}$  = No. speech and  $X_j$

$n_{-j,p}$  = No. press and not  $X_j$

$n_{-j,s}$  = No. speech and not  $X_j$

# A Method for Identifying Distinguishing Words

Formula for Mutual Information

$$\begin{aligned} \text{MI}(X_j) = & \frac{n_{j,p}}{D} \log_2 \frac{n_{j,p}D}{n_j n_p} + \frac{n_{j,s}}{D} \log_2 \frac{n_{j,s}D}{n_j n_s} \\ & + \frac{n_{-j,p}}{D} \log_2 \frac{n_{-j,p}D}{n_{-j} n_p} + \frac{n_{-j,s}}{D} \log_2 \frac{n_{-j,s}D}{n_{-j} n_s}. \end{aligned}$$



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# Objective Function

Suppose we're interested in how a word separates partisan speech.

$\mathbf{Y} = (\text{Republican}, \text{Republican}, \text{Democrat}, \dots, \text{Republican})$

$\mathbf{X} =$  Unnormalized matrix of word counts  $N \times J$

Define

$$\begin{aligned} \mathbf{x}_{\text{Republican}} = & \left( \sum_{i=1}^N I(Y_i = \text{Republican})X_{i1}, \sum_{i=1}^N I(Y_i = \text{Republican})X_{i2}, \right. \\ & \left. \dots, \sum_{i=1}^N I(Y_i = \text{Republican})X_{iJ} \right) \end{aligned}$$

with  $N_{\text{Republican}} =$  Total number of Republican words

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This implies an objective function on  $\boldsymbol{\pi}$ ,

$$p(\boldsymbol{\pi} | \boldsymbol{\alpha}, \mathbf{X}, \mathbf{Y}) \propto p(\boldsymbol{\pi} | \boldsymbol{\alpha}) p(\mathbf{x}_{\text{Republican}} | \boldsymbol{\pi} \boldsymbol{\alpha}, \mathbf{Y})$$

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$$\pi_{\text{Republican},j}^* = \frac{x_{\text{Republican},j} + \alpha_j}{N_{\text{Republican}} + \sum_{j=1}^J \alpha_j}$$

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# Calculating Log Odds Ratio

Define log Odds Ratio<sub>j</sub> as

$$\text{log Odds Ratio}_j = \log \left( \frac{\pi_{\text{Republican},j}}{1 - \pi_{\text{Republican},j}} \right) - \log \left( \frac{\pi_{\text{Democratic},j}}{1 - \pi_{\text{Democratic},j}} \right)$$

$$\text{Var}(\text{log Odds Ratio}_j) \approx \frac{1}{x_{jD} + \alpha_j} + \frac{1}{x_{jR} + \alpha_j}$$

$$\text{Std. Log Odds}_j = \frac{\text{log Odds Ratio}_j}{\sqrt{\text{Var}(\text{log Odds Ratio}_j)}}$$

# Applying the Model

<https://gist.github.com/thiagomarzagao/5851207>

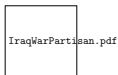
How do Republicans and Democrats differ in debate?

Condition on **topic** and examine word usage

- Press Releases (64,033)
- Topic Coded
- Given press release is about topic, what are the features that distinguish Republican and Democratic language?



## Mutual Information, Standardized Log Odds



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# Gentzkow, Shapiro, and Taddy (2017): Rhetorical Polarization

